A BIOMIMICRY APPROACH TO AUTOMATION OF ROAD FEATURE SURVEYS

by

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For my late father,

my beloved mother,

and my wife.

Signed Statements

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ABSTRACT

Australia's road network is a very significant capital asset created by progressive investment over several decades, and is integral to the social and economic performance of the nation. Physical elements of the road infrastructure are numerous and include surfacing, bridges, lighting, signs and line-markings.

Road condition assessment is critical to optimisation of both road performance and public investment strategies. Road condition data are of fundamental importance if a road owner is to demonstrate that best practice road management is being followed in line with investment and budgetary constraints. Road surveys that are able to quickly and efficiently identify features and assess their condition are therefore keystones of an effective road asset management system. Manual visual surveys are subjective and expensive, while digital imagery and off-the-shelf computer hardware and software packages have the potential to carry out image analysis in real time. This in turn has triggered a surge of interest in the possibility of automating road survey systems.

Efforts to date have stopped short of producing such survey systems. This research was motivated by a desire to understand why this is so, and to explore the way forward. The thesis therefore starts with a general review of the current condition of road assets in Australia, and the manual and semi-automated road condition survey systems widely used by asset managers. The key problems appear to be the difficulties in producing survey systems for quite different applications and survey conditions. Biomimicry suggests that a way forward might be to identify a generic system design, rather than seek to develop a single do-all survey system.

The thesis then examines the suite of image processing and artificial intelligence tools, including expert systems and neural networks, that have become available to help automate such surveys. A generic design approach is proposed to develop automated road feature and condition survey systems, together with design application principles that are also largely inspired by biomimicry. The three principal system components are:

1. Image acquisition, which mimics the work of the eyes.
2. Image processing that parallels the work of the visual cortex.
3. Feature recognition and condition assessment that mimic the cognitive aspects of a human brain, notably its biological neural networks.

Analysis of the survey results, if necessary, constitutes a fourth system component. This often involves consideration of context and/or aggregation of information into one or more overall road condition indicators. Expert rule systems are ideally suited to such tasks.

A two-stage survey development process is proposed. First, a *basic* survey system is developed which performs well under ideal survey conditions, with the goal of understanding and establishing the fundamental aspects of the survey system. Next, an *extended* survey system is developed that can handle the more complex, non-ideal survey environments that must be addressed in an actual survey of a long stretch of rural highway. The extended survey system development process starts by examining the performance problems of a basic survey system applied to the more challenging survey conditions.

The system design is illustrated by case studies of guidepost counting and centreline-marking condition assessment. The satisfactory performance of the basic automated systems for these applications is demonstrated using typical sections of road. An extended system for guidepost counting is then produced and its performance examined on a survey of the Midland Highway in Tasmania. The thesis concludes by discussing how best to develop these automated systems into an operational tool through trials carried out in association with local government and road authorities.

Case studies are presented to demonstrate the basic survey system development process applied to guidepost counting and to evaluate centreline-marking condition. The approach to developing an extended survey system is demonstrated to produce an improved guidepost survey system able to deal with changing ambient light conditions. The satisfactory performance of this extended system under non-ideal conditions is confirmed via a 50 km field trial on a section of the national highway in Tasmania.

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A BIOMIMICRY APPROACH TO AUTOMATION OF ROAD FEATURE SURVEYS

CONTENTS

1.0 INTRODUCTION

1.1 Background

The range of public infrastructure managed by the three levels of Australian government is very extensive. It includes the road system network, bridges, trunk main and reticulation hydraulic systems, reservoirs, associated treatment plants and pumping stations, parks, reserves and playground equipment, buildings, and infrastructure plant and equipment (GMS & ASDCS, 2001).

In order to enable governments to deliver services to the community, enormous investment has been made in these assets, especially in the national and state highway network, which was identified to have a total value in 1995 of $92 billion (IEAust & GHD, 2003). These assets, held long-term, attract liabilities in terms of the costs for ongoing operation and maintenance. They should be managed in the most cost-effective way for the entirety of their operational life (INGENIUM, 2002).

One of the most significant challenges to the viability of good government thus relates to the management of infrastructure assets. As a large portfolio of infrastructure has been built over the last three decades, governments have shifted their asset management strategies from building new assets towards maintaining and looking after the existing assets (NSW PWD, 1993). There is increasing realisation that existing infrastructure assets historically have not been adequately maintained. These assets are deteriorating, and rigorous assessment, constant maintenance and management are required in order to ensure that they can be sustained, and to allow the government to continue to foster growth (NSW PWD, 1993).

The 1999 report card by Engineers Australia on the nation's infrastructure (IEAust & GHD, 2003) ranked the condition and management of Australia's existing infrastructure between adequate and poor, and the 2001 report card indicated that not much improvement had been achieved to that time (EA, 2003). For road assets as an example, several surveys summarised in EA (2001) showed that more than half of the regional and local roads were rated as "average" or "less than average", or regarded as unsafe in 2001. Although the 2005 report card (EA, 2005) showed that the condition of these assets had slightly improved, parts of these assets are ageing and nearing the end of their economically useful lives, and adequate expenditure is required to renew or maintain them at an acceptable standard.

There is an increasing emphasis on the importance of asset management in order to obtain the best value for money from existing infrastructure and to avoid a recurrence of the deterioration of these assets such as occurred over the last decade. In addition, there have been increased efforts to implement strategic management systems for infrastructure assets, particularly the road system, as transportation is probably the most dominant asset group and is one of the most visible to the public.

Condition surveys are essential keystones for an effective road management system. Monitoring of road condition is undertaken to save costs caused by asset degradation, and to increase safety for road users. However, traditional visual assessment is subjective and labour intensive. With the advent of digital imagery, and off-the-shelf computer hardware and software packages that can carry out image processing and analysis in real time, there has been a surge of interest in the possibility of automating road condition assessments, using tools such as image-based artificial intelligence systems.

Artificial intelligence systems are becoming widely recognised as powerful and elegant tools suitable for many engineering applications. The principal tools of artificial intelligence used in this research are expert systems and neural networks, as shown in Figure 1.1. Expert systems mimic how people make decisions, and hence provide a natural way of thinking for decision-making. Neural networks are used to perform complex functions in engineering applications involving pattern recognition, feature classification, and various prediction problems such as road traffic noise (Doolan & Carter, 2005). The integration of image processing and artificial intelligenge methods to assist pavement maintenance management processes is illustrated in Figure 1.1. These methods are described in detail in Chapter 3 of this thesis.

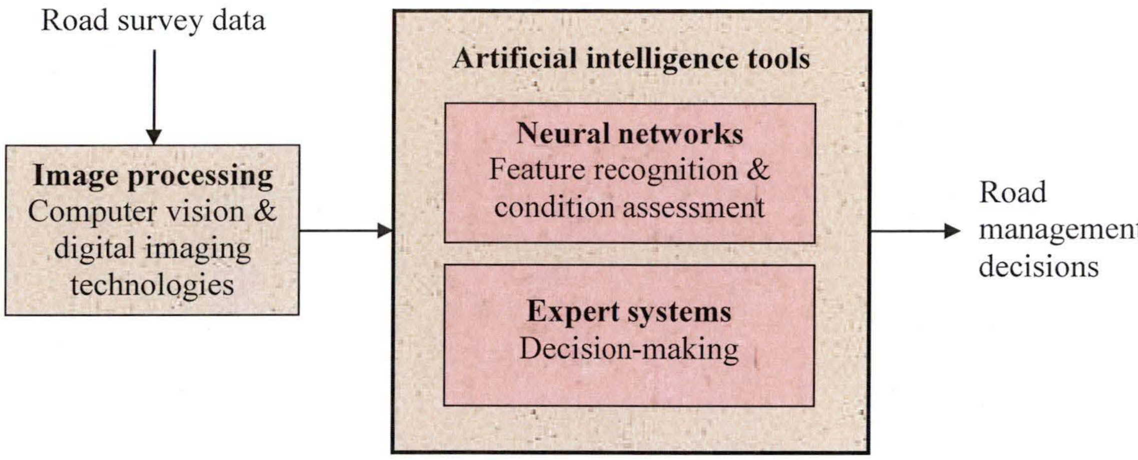


Figure 1.1: Applications of image processing and artificial intelligence systems to road asset management

1.2 Research Motivation and Goal

This research has been motivated by the author's desire to find a way to automate and more effectively assess the condition of road infrastructure assets in real time. Tools such as image processing techniques and artificial intelligence systems have been available for some years, and have clear potential to automate road survey and condition assessment. In addition, the hardware and software components of an automated survey system are available as off-the-shelf items. The key question is therefore why has the industry stopped short of developing fully automated survey systems? Why have such automated systems not been produced? The research started by seeking an answer to this question, with the goal of identifying a way to overcome the problem.

1.3 Research Strategy

This research was sponsored by the Civil Construction Corporation and subsequently by Works Infrastructure of Downer EDI, and was supervised by Dr. Steve Carter and Professor Frank Bullen. Dr. Carter is a consultant environmental engineer, and a lecturer in the School of Engineering at the University of Tasmania. Professor

Bullen is the Head of the School of Engineering. The research required the author to acquire first-hand asset management experience, and this was achieved by working with Mr. Brian Edwards, who acted as a research advisor. Mr. Edwards was then the asset manager with the Hobart City Council.

The first step in the research was to review existing road survey methods. The results of this review are presented in Chapter 2, and the clear conclusion of the review was that the main barrier to automating survey systems was the difficulty in producing a system able to handle the wide range of possible applications. It was determined that identifying a generic design approach might provide a platform from which to establish automated road survey systems for specific applications, a conclusion reached by examining the way in which nature has solved similar problems.

Chapter 3 reviews the tools needed for such automated visual survey systems, namely image processing and artificial intelligence tools, together with hardware and interface requirements. The Matlab engineering and scientific computing platform, produced by The MathWorks, was adopted in this research because of its excellent image processing and artificial intelligence toolboxes. Other software packages are available, but Matlab is widely used by the engineering profession.

Chapter 4 presents a generic system design to underpin automated road survey systems. The design is inspired by biomimicry, and the design application principles discussed in the chapter also draw heavily on biomimicry. A key aspect of the development process is to first establish a *basic* survey system for a given application, that performs well under ideal survey conditions and incorporates the fundamental requirements of the system. An *extended* system, or systems, can then be produced to handle more complex surveys, such as those which must deal with changing conditions.

Chapter 5 illustrates the system design approach by applying it to a feature identification case study. A basic survey system is developed to identify roadside guideposts. The system's performance is verified using information obtained from a manual inspection, and its limitations under more complex survey conditions are examined.

Chapter 6 presents a second case study, in which another basic survey system is developed, this time to assess the condition of line-marking. The system's performance is again verified using the information obtained from a manual inspection, and its limitations under more complex survey conditions are examined. Follow-on analysis has also been carried out to include an expert system to consider road context during condition survey.

Chapter 7 extends the basic guidepost survey system described in Chapter 5 to include a supervisory module, such that the survey system can perform adequately under more complex and changing survey conditions. The chapter also presents the results of a 50 km field trial of the guidepost survey system, and these results are most promising.

Chapter 8 sets out the conclusions of the research, discusses the importance of automated survey systems to asset management, and possible future system development directions.

2.0 VISUAL ASSESSMENT OF ROAD INFRASTRUCTURE

2.1 Asset Management

Austroads (1995) defined asset management as "*a comprehensive and structured approach to the whole of life management of assets as tools for the cost of efficient and effective delivery of government services, with management decisions to create, maintain, operate, modify, repair or dispose of assets based on the total costs and quality of service provided by the asset, to provide for present and future members of the community through a combination of technical, financial and strategic management*". Many other definitions exist but all incorporate recognition that the process is cyclic as shown in Figure 2.1.

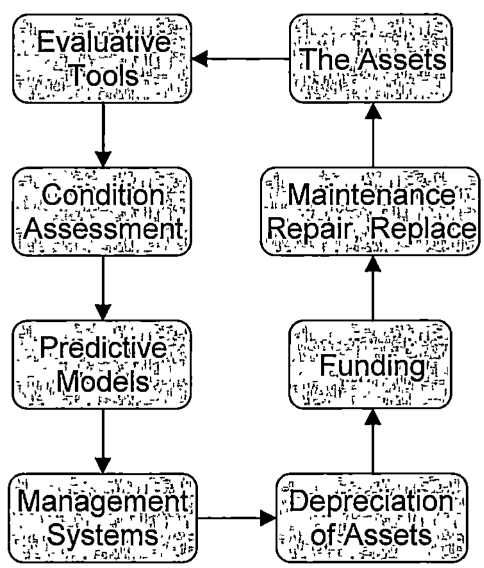


Figure 2.1: A schematic representation of the asset management cycle (Ng et al., 2006)

FHWA (1999) noted that asset management draws from economics as well as engineering, and generally provides a way of efficiently allocating funds among valid and competing needs. According to GMS & ASDCS (2001), asset management is an essential part of good business practice, that seeks to define critical service standards and measures, then determines plans to most cost effectively meet the strategic objectives for the short and long term. Figure 2.2 summarises factors that influence this objective (Prabhu, 2002b).

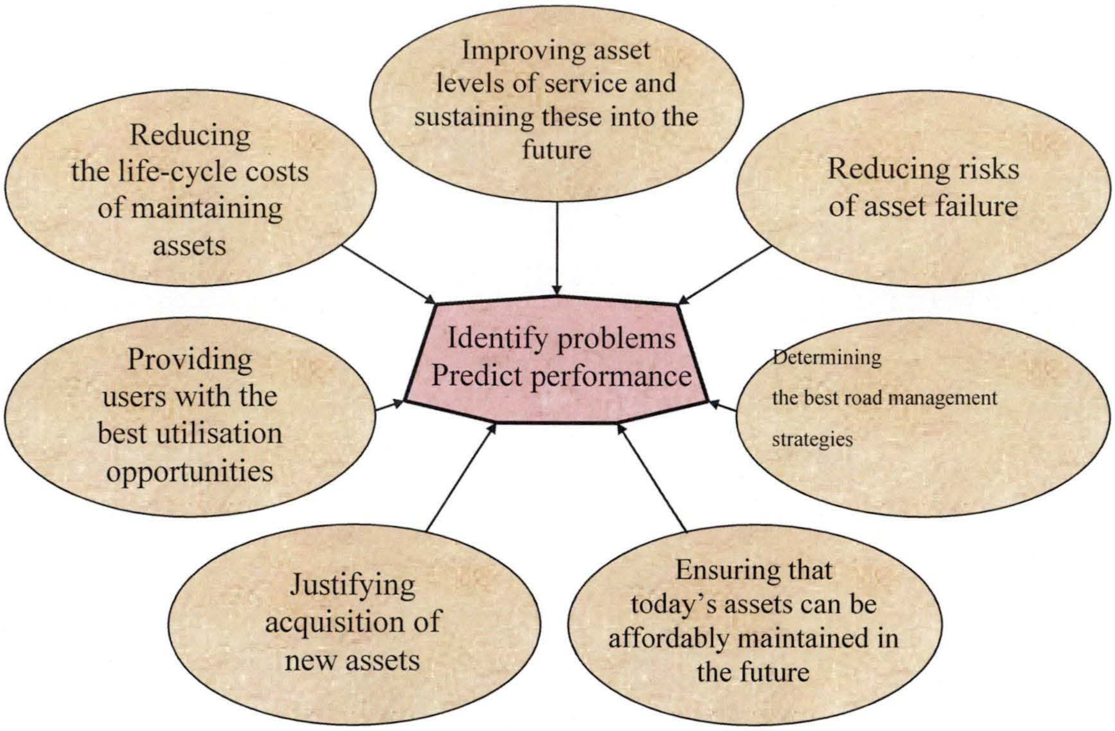


Figure 2.2: Asset management focuses and associated issues (Prabhu, 2002b)

Asset management aims to ensure that assets are sustainable. In order to achieve this, management decisions need to be defensible, and the long-term impacts of short-term decisions need to be clearly demonstrated, such that an asset operates and is maintained in an appropriate fashion and in a satisfactory condition. In addition, GMS & ASDCS (2001) suggested that state governments and local councils continue to develop and operate formal asset management practices, and to provide sufficient funds to maximise the utilisation and functionality of their assets.

A management strategy relating to an asset is thus necessary to provide a long-term or life-cycle outlook. It needs to form a basis for decision-making, including planning, design, construction, rehabilitation, maintenance and budgeting through an asset's life-cycle (Austroads, 2002; Howard, 2001; Parnell, 2001).

The techniques of "whole of life" management of assets enable a logical approach to balancing maintenance, upgrade and renewal decisions. This encompasses planning and applying physical treatments to an asset and controlling its use so that its features and condition combine to best serve the community (Austroads, 2002; IEAust & GHD, 2003).

2.2 Road Infrastructure Management

Australia's road network is a major component of the nation's transport and communication infrastructure. Road assets include physical elements such as surfacing, bridges, footpaths, bicycle paths, drainage, lighting, sign and line-markings, traffic control signals, and retaining walls. In addition, road reserve management emerged in the 1990s as a leading environmental issue, with the remnant vegetation associated with road reserves often containing threatened species and providing habitat for fauna (Duckett, 2002).

The Australian road network is a capital asset created by progressive investment over several generations, and it is integral to the social and economic performance of the nation (Austroads, 1994). Table 2.1 summarises the value of Australia's road network in 2000, which consists of more than 800,000 km of public road, of which about 40% is bituminous or concrete surface (RoadFacts, 2005).

- National highway - Rural local - Rural Arterial - Urban local - Urban arterial Total length	19,000 km 601,000 km 95,000 km 85,000 km 12,000 km 812,000 km
Total value (2000)	$92 billion
Annual road expenditure - Extension and improvement (40%) - Maintenance (60%)	$6.2 billion

Table 2.1: Australia's road value (IEAust & GHD, 2003)

Considering Tasmania as a case study, the state's road network is substantially mature, and consists of about 3,500 km of State and Commonwealth owned roads with 1,200 bridges, and about 12,000 km of roads with 3,800 bridges for which local government is responsible. The State Government allocated about \$52 million for roads and bridges in 2003 (Rose, 2004). In 2005, more than \$90 million was spent on Tasmania's roads, including \$60 million from the state-generated funding for road upgrades and \$30 million from the Federal Government for highways (Choy, 2004). Figure 2.3 shows the value in 2004 of road assets managed by the Hobart City Council (HCC), the largest Tasmanian council.

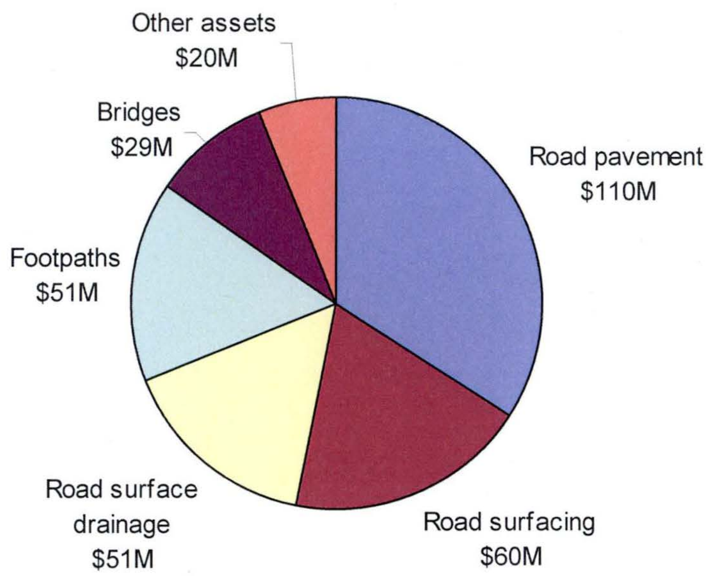


Figure 2.3: Value of road assets managed by HCC in 2004 (HCC, 2004)

The Australian road transport industry is experiencing a cultural change in the way its assets are managed. In the 1990s, the interest in road planning shifted from an almost exclusive focus on construction to a more strategic approach, which included planning of maintenance and rehabilitation of existing road assets. This occurred due to the ageing of the road network, the increasing management pressures to improve road system performance, the introduction of commercial accounting practices, and budgetary constraints (Austroads, 1995; Bennie & Drummy, 2001). This trend has continued to the present.

The Australian Sustainable Energy Transport Taskforce noted that all existing transport infrastructure is under pressure as a result of increased demand and lack of investment and funding (IEAust, 1999; Kirby, 2001). In fact, inadequate funding has remained a major issue in many states, such as New South Wales (EA, 2003), Victoria (AGVic, 2003), and Tasmania (Wade, 2004).

Better management of the road network has emerged in response to a growing recognition of the need for road managers to focus on strategic management of road networks, with increased emphasis on user perspective. Due to the rising costs of maintaining assets and the long-term impacts of short-term decisions, road authorities are looking for innovative ways to manage infrastructure assets. A growing need for demonstrating sustainability in the maintenance of assets has also led to the necessity of implementing structured asset management systems (Prabhu, 2002a). However, the lack of consistent and consolidated data, and the lack of standardised asset management databases have long been a problem, especially for local road networks (EA, 2001; Howard, 2002).

To ensure the sustainability of road assets, good tools are required to assess the physical condition of the assets. Other key issues associated with road management include decision-making and optimisation, which also rely on condition assessment.

2.3 Role and Nature of Condition Assessment

Road condition assessment is one of the main inputs to determining and characterising road performance over time. A road's physical condition, and the public acceptance of that condition, can fluctuate considerably over its useful life as demographics change. The trigger for maintenance and capital expenditure is when the condition of the road approaches an "unacceptable" level, either in terms of its service performance, or in terms of safety issues.

Most road management decisions rely on understanding the condition of road assets as well as the rate of change of condition, and where the road is in its life-cycle. Figure 2.4 shows a typical asset life-cycle deterioration curve. Understanding the rate of change of condition with time, as a consequence of environmental factors and/or usage, enables assessment of management options, particularly regarding maintenance. It also helps to determine the remaining life of road assets (Austroads, 2003b). It is thus essential to measure and monitor a road's condition, and to understand the relationship between the condition of road components and performance measures.

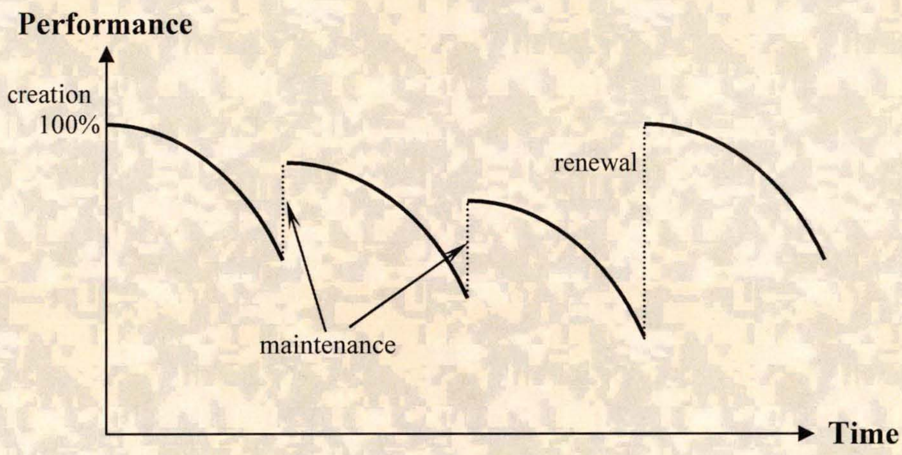


Figure 2.4: A typical asset life-cycle chart (Prabhu, 2002b)

A road condition assessment exercise measures the nature and extent of any gap between the actual and required conditions of the road, based on pre-defined criteria. If there is a significant difference, there is likely to be an impact on the operation of the asset, and there may also be financial and legal impacts. These need to be clearly identified for decision-makers (VIC DPD, 1996).

Through condition assessment surveys, a road's condition can be translated into data describing the physical characteristics of the road, such as surface wear and tear, material fatigue and degradation, structural and safety data. Road condition data can be analysed to determine the value of the asset, and to allow decisions to be made about its maintenance and associated budget expenditure (VIC DPD, 1996). Road condition data also underpin the concept of service pricing, whereby road users such as B-double operators are allowed to carry additional freight in exchange for payment of a road maintenance fee. This is the basis of so-called Intelligent Access systems (DIER, 2003; Austroads, 2003a, 2004).

Road condition data are gathered in accordance with set protocols for different features, some of which are quite detailed. For example, in surveys of road line-marking, the condition rating (i.e. degree of paint wear) is determined by comparison of the line-marking with a number of photographic references. In Australia, a reference used by several states is ROCOND (1990), which is a 5 point scale ranging from 1 (excellent condition) to 5 (bad condition). Supporting an appraisal of road marking condition by identifying the life of the paint, can reduce maintenance costs by avoiding premature remarking.

Assessment of road cracking provides another illustration of the importance of condition assessment. Road cracking should be detected and addressed as early as possible, since significant savings can be made if treatments are applied sufficiently early in the cracking cycle to prevent moisture ingress and subsequent accelerated degradation (Ferguson & Pratt, 2002).

Other protocols address texture loss, surface distortion, disintegration and shoulder erosion. The individual feature assessments can be aggregated into an overall "score" to represent the condition for each road segment.

The frequency of condition assessment depends on the confidence in the measurements being made, the level of funding available, and the cost effectiveness of the assessment process. The process needs to ensure that the assessment captures any significant changes in asset condition based on asset complexity, age, location, usage and environmental factors. However, to ensure that risks to the public and legal liability are minimised, and to ensure that crash costs are reduced or avoided by timely maintenance, road assets should be inspected at an adequate frequency to identify defects that may represent a hazard (GMS & ASDCS, 2001; Austroads, 1995).

In Queensland, the state government and local councils carry out inspections every one to two years on higher function arterial and secondary roads; every three years on lower function secondary, collector and access roads; and on an annual basis on unsealed roads (Main Roads, 2004). The level of inspection (i.e. detail) varies according to the road class.

In Victoria, pavement condition surveys for state roads are conducted bi-annually on declared roads, and annually for a selected sample of all roads to provide a benchmark for assessment of annual changes in the condition of roads in different parts of the state (VicRoads, 2004). VicRoads compares the results from annual road condition surveys to maintenance standards and performance targets to identify gaps in road asset performance. A detailed inspection of all features identified as potential problems is then carried out, to determine the most cost effective treatment for managing those gaps, and to properly scope each project. For example, potholes that exceed 300 mm diameter and 150 mm in depth in sealed pavements should be filled to improve service performance and user safety (VicRoads, 2004).

Condition data should be consistent, repeatable, reliable and relevant, and lead to better decision-making. To ensure this, condition needs to be measured by a systematic method that ensures robustness, repeatability, and is cost-effective.

Robustness means that condition should be measured in such a way that it can correctly indicate whether work is required, by referring to the intervention levels of the asset. *Repeatability* means that the same condition assessment can be obtained from the same road segment by more than one person or machine on different occasions. In determining performance trends, data have to be repeatable to ensure that real performance is established. To ensure repeatability, the assessment method should be kept simple enough to satisfy end objectives without sacrificing accuracy (Lundkvist, 2003). *Cost-effective* means the cost of gathering the data is considered to be money well spent because the data enables better planning of road maintenance work in terms of timing and focus of the work.

Road features can be classified into visually and non-visually assessed features. Non-visually assessed features include roughness, rutting, quality of patching, deflection under load, bituminous binder condition, material quality and skid resistance (Austroads, 1994). Field and laboratory methods to assess such features are well established (VicRoads, 1993), as shown in Table 2.2. Some features, such as mechanical roughness, can be assessed by specialist vehicles equipped with remote sensing equipment or a multi-laser profiler (Ryan, 2002), and are particularly useful in characterising long uninterrupted stretches of road such as highways and some major arterial roads. The use of sampling is sometimes used to reduce the cost of the survey, albeit with an associated loss in accuracy.

• roughness meter	• portable texture meter
• profilometer	• Benkelman Beam
• deflectograph	• falling weight deflectometer
• elastic modulus test	• in-situ pavement investigations
• pendulum meters	• high speed skid resistance testing vehicles
• texture meters	• sampling of pavement materials

Table 2.2: Non-visual assessment methods

This research focuses on road features that can be assessed visually, although it is always important to supplement visual information with other measurements where appropriate. Visual condition assessments involve exercises such as assessing guidepost numbers, road surface cracking, the quality of line-markings, the extent of edge breaks, and the condition of roadside vegetation. The manual inspection team (usually two inspectors) often conducts a full "fence-to-fence" road corridor inspection for each highway section in one pass.

2.4 Present Visual Condition Assessment Methods

2.4.1 Manual Inspection

The nature of visual inspection tends to be different between urban roads and rural highways. Urban roads are much shorter and more complex, and they do not take so long to be surveyed. This research focuses on rural highways, which are common in countries like Australia and Canada. Such rural highways can stretch for hundreds of kilometers: surveys take many hours to cover the target length of highway, and can be subject to changes in the weather and other survey conditions.

The method used by most Australian road authorities to visually assess the conditions of road features is a survey undertaken manually by experienced inspectors. Visual surveys involve the detailed rating of road segments by travelling the road and evaluating each condition variable against a set of defined criteria. Condition parameters are often converted into indices to enable the application of semi-quantitative ratings, and to assist in working out priorities in different sections or in monitoring deterioration (Narendranathan et al., 2001). References for manual condition assessment in Australia are ROCOND (1990), NAASRA (1987) and Austroads (1990, 2001a, 2001b).

The example of line-marking was given in the previous section. As another example, Table 2.3 shows a rating scale for pavement condition with respect to surface defects.

Condition rating	**Affected portion of the segment's total trafficable area**
1	< 1 %
2	1 - 5 %
3	5 - 10 %
4	10 - 20 %
5	> 20 %

Table 2.3: Condition rating for surface defects (ROCOND, 1990)

During a visual survey, road condition ratings are recorded on a worksheet, noting the severity and extent of any problems, where *severity* refers to the degree of road deterioration; and *extent* refers to the frequency of occurrence or amount of road surface (length or area) affected by the problem (Kercher, 2002). Different road features require different assessment procedures.

Figures 2.5 and 2.6 show typical worksheets used during road surveys of pavement cracking, surface defects, and road profile.

		1 of 1

Road name:.. Road number:..............................

Assessor 1 name:.. Date of survey:.............................
dd/mm/yy

Assessor 2 name:..

Weather conditions (circle):

Rain	Showers	Dry	Cold	Warm	Hot

Chainage		Segment number (e.g. Roadloc Code)	Carriage-way code (A,B,C,L,R, M,P,Q)	Sealed/ unsealed	Roughness/ ride quality/ driveability rating (1-5)	Rutting rating for sealed roads (1-5)	Local surface defects for sealed roads (1-5)	Road profile for unsealed roads rating (1-5)	Additional defects (specify)			Comments
km	From reference point											

Figure 2.5: A typical road pavement condition worksheet (Main Roads, 2004)

		1 of 1

FOR SURFACE TYPE – SPRAYED SEAL, ASPHALTIC OR GRAVEL

Road name: .... Segment: ....

Assessor name: .... Date..............................

Rutting for sealed roads (manual method)

Readings										>5 mm	(T)
										No. >5 mm	(N)

Severity S = < 10 mm M = 10 - < 20 mm X = > 20 mm	Extent 0 = < 10% 1 = 10 - < 15% 2 = 15 < 20% 3 = > 20% -1 = not applicable
Severity $\frac{\text{Total} > 5\text{mm}}{\text{Number} > 5\text{mm}} = \frac{(T)}{(N)} =$ ______ mm Code [ ] Pavement rutting distress code = ______________	Extent 3.3% * (N) ______________ % Code [ ]

Local surface defects (per lane)

Width (W)	Patches length (L)	Total length (TL)	Area (TL * W)	Condition score
0.5				1 = 0 < 1% 2 = 1 - < 5% 3 = 5 - < 10% 4 = 10 – 20% 5 = > 20%
1.0				
1.5				
2.0				
Lane				
		Total		

$\frac{\text{Surface Defects Total Area}}{\text{Segment Total Area}} =$ $\frac{*100}{1} =$ .....%

Code = [ ]

Road profile /cross section for unsealed roads

Rating (R)	Lengths along segment (m)	Total lengths (TL)	Score (Rating R * Total Length TL) (S)
1			
2			
3			
4			
5			
	Total		

$$\text{Average Rating} = \frac{\text{Score (S)}}{\text{Total Length (TL)}} =$$

Figure 2.6: Another typical road condition inspection worksheet (Main Roads, 2004)

In Tasmania, the state government carries out visual surveys of its rural highways using a patrol vehicle, inspecting pavement features such as cracking, line-marking, and surface defects; and the condition of road furniture such as road signs, guardrails, and guideposts.

Although manual inspection is the most popular method of conducting visual surveys, this method is labour intensive if the road to be surveyed is a few hundred kilometers in length, such as a rural highway. Mundy & Richards (1992) and Harris (2002) argue that manual assessment methods can hardly produce reliable results, as they are prone to human error or bias, especially if an inspector is inexperienced. It is difficult to accurately and consistently assess road conditions in the field, especially if a road is in poor condition. Once one section of road has been given a certain condition rating, the inspector may unwittingly tend to apply the same or similar ratings to subsequent sections. In other words, consistency of ratings, and perhaps pre-conceived expectations of a road's condition may influence an inspector's decision regarding the condition rating of each section of road. These factors can exacerbate a variation in condition ratings determined by consecutive surveys, suggesting that manual methods are not as repeatable as would be wished.

Discrete condition rating criteria generate an additional source of survey inconsistencies, compared to continuous rate criteria. Figure 2.7 illustrates this point using a matrix based on a standard risk assessment table to determine maintenance priority from two inputs (AS/NZS 4360, 1999).

Safety risk	**Condition**				
	Excellent	Good	Moderate	Poor	Bad
Very high	High	High	Extreme	Extreme	Extreme
High	Moderate	High	High	Extreme	Extreme
Moderate	Low	Moderate	High	Extreme	Extreme
Low	Low	Low	Moderate	High	Extreme
Very low	Low	Low	Moderate	High	High

Figure 2.7: A discrete maintenance priority rating matrix

In Figure 2.7, the two inputs to the maintenance priority matrix are the physical condition of the road feature, and the associated safety risk. The matrix is a "decision surface" that consists of steps. The red and blue dots in the table show that small differences in the inputs can make a significant difference to the evaluation of the maintenance priority, in this case a jump from low priority to high priority.

It should be noted here that a smooth decision surface can easily be produced using an expert system. The expert system takes the same inputs as the matrix, but calculates the maintenance priority using fuzzy logic, resulting in a continuous, smooth decision surface instead of one characterised by steps separated by jumps from one priority to another. The nature of expert systems is discussed in Chapter 3.

As reliable and objective data are required for works planning by contractors and for performance measurement by clients, condition surveys need to be accurate to ensure that the proper management strategy is selected for each road segment. Inaccurate or wrongly interpreted data will lead to inappropriate repair strategies that ultimately result in the inefficient and inappropriate allocation and use of funding. As most of the inaccuracies and limitations of manual assessment are operator-induced, a more reproducible and objective method is needed.

2.4.2 Video and Digital Technology

Over the last decade, visual road surveys have been facilitated by the use of videos and digital imagery that allows camera images to be stored for later desk-top analysis by inspectors. Although digital imaging technology has only been implemented by a handful of councils in Australia to date, it is clearly a powerful and cost-effective aid to road surveys. Archival images can be used to meet risk management, maintenance or operational needs, by enabling comparison of the present and past condition of road features such as signage, pavement surface, and roadside vegetation.

Image recording and analysis technology facilitates objective and accurate assessment of road features such as cracking and roadside vegetation. It has been proven to be both repeatable and auditable (Thomson & O'Brien, 2003). It can lower the field man-hour component by minimising the total time required to assess the road condition. It can also reduce the inconvenience to road users and associated safety issues during road surveys. With a digital imaging system, data capture and assessment can be directly overseen and managed.

Digital imaging systems that fit within an existing data centric asset management model, such as that used by the Blue Mountain City Council (BMCC) of New South Wales (Figure 2.8), facilitate the management of an extensive infrastructure network, and improve the accessibility to information for various stakeholders and the speed and accuracy of data capture. However, the "condition assessment" box in Figure 2.8 retains the manual assessment approach.

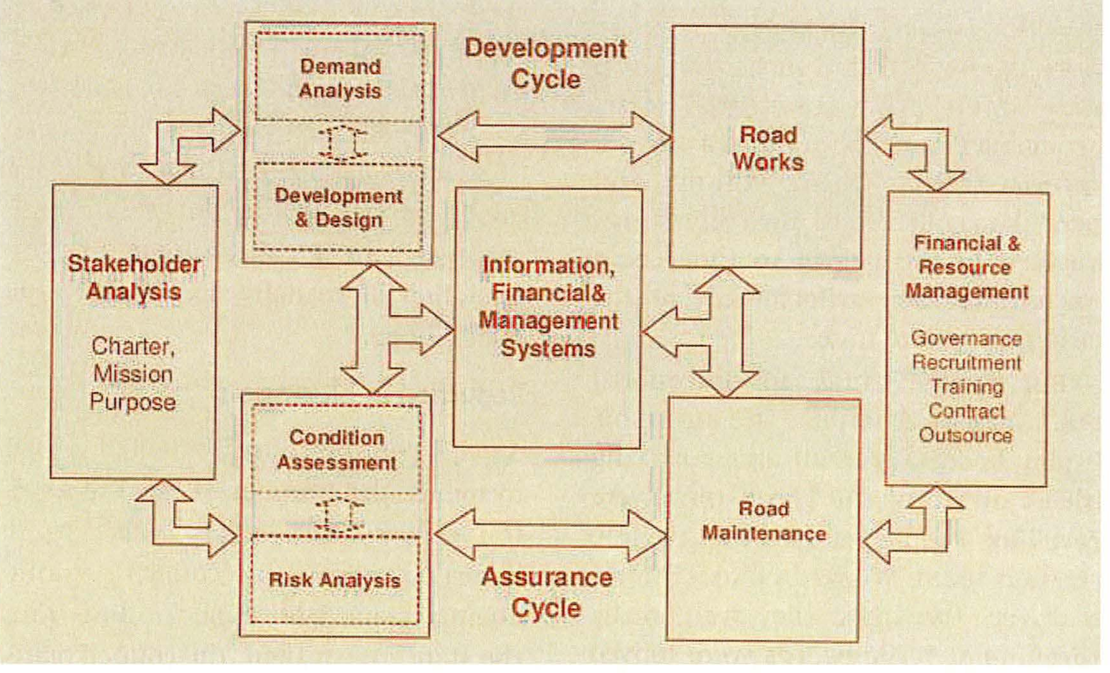


Figure 2.8: BMCC data centric road asset management model (Thomson & O'Brien, 2003)

2.4.3 Examples of Assessment Systems

Experimentation with video and digital technology in road condition surveys has been undertaken by several road authorities in Australia. The following sections provide examples of semi-automation of image-based condition survey and assessment processes.

Measurement of road marking paint wear by SA DRT

The South Australia Department of Road Transport (SA DRT) uses digital image analysis to measure the wear of road marking paint lines (Mundy & Richards, 1992). The technique employs the use of imaging techniques on digitised images of photographs taken of the worn paint line segment. A video recorder is used to provide images of paint line-markings to be input to a computer. Subsequent imaging methods are then used to enhance the areas of concern so that measurements of the road features are meaningful.

A special camera setup is used to ensure that the photographs obtained are of high quality and consistency, and each colour print is uniformly matched with a scale and chart, for repeatability. This can produce a consistent quality print and enable a quality image to be analysed. Each pixel in a digital image is associated with a greyscale. The image is formed by thousands of different greyscale value pixels, with a frequency distribution of all values obtained from one image. The condition of the paint line in each image is assessed by comparing the frequency distribution to a specific scale.

This technique can provide a repeatable means of measuring the wear of road marking paint. However, the technique is not automated, and is thus user-intensive.

Detection of pavement cracking by NSW RTA

The *RoadCrack* vehicle, shown in Figure 2.9, uses a real-time imaging system developed by the CSIRO. It is used by the New South Wales Roads and Traffic Authority (NSW RTA) to automate the detection and classification of cracking in road pavements (Ferguson & Pratt, 2002).

RoadCrack uses a high speed image acquisition system to collect and transfer a continuous flow of image data from the cameras to the machine vision module. This

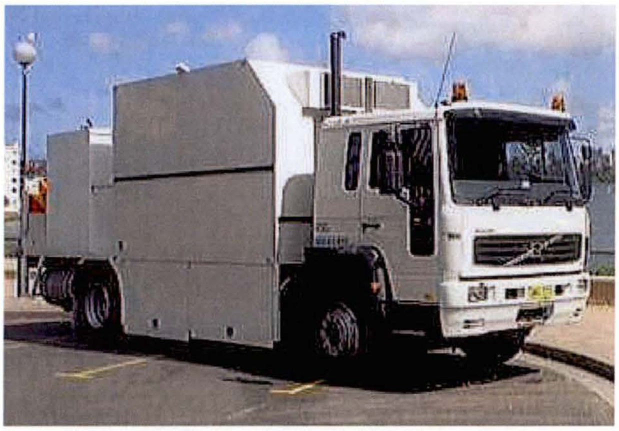


Figure 2.9: Multi-channel *RoadCrack* vehicle used by the NSW RTA

allows data to be routinely gathered at highway speeds to determine the extent of cracking. The image processing module within the system is capable of detecting and reporting the predominant cracking type and the cracking severity. *RoadCrack* analyses images in real time using high speed parallel CPUs.

ARRB road condition survey vehicles

ARRB Transport Research has developed a range of vehicle mounted measuring devices to assist road condition surveys. As shown in Figure 2.10, the ARRB multi-channel digital imaging system mounted on top of a vehicle allows a digital imaging survey to be carried out at high-speed with permanent images recorded along the entire length of road together with ancillary information (ARRB, 2001, 2003).

Figure 2.10: Vehicle with multi-channel digital imaging system used by ARRB

The system has been used by other countries, such as Malaysia (PAVES, 2003). It captures visual information about road condition, pavement distress and roadside features, using a multi-channel image acquisition system with a real-time differential global positioning system option. It can be integrated into a customised survey vehicle to allow the collection of all data in a single system.

Figure 2.11 shows the multi-channel image viewer software designed by ARRB to view up to four channels of digital images captured by the system. These channels display the pavement view, the forward view, the driver side view and the passenger side view, as shown in the secondary panel on the top right corner of Figure 2.11, and enlarged in Figure 2.12. The images can be viewed frame-by-frame or played continuously with a defined time interval between each frame, and the road condition can be assessed manually using visual inspection.

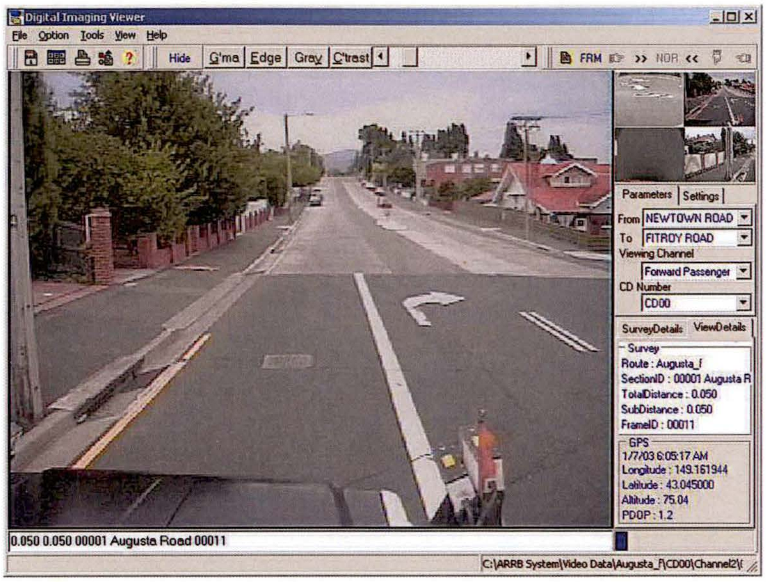


Figure 2.11: Multi-channel Image Viewer designed by ARRB, used in conjunction with the multi-channel digital imaging system

Figure 2.12: Four channels of images captured by the ARRB digital imaging system at the same time
(Upper left: Driver side view; Upper right: Forward view;
Lower left: Pavement view; Lower right: Passenger side view)

PMS road condition survey system

The survey system developed by Pavement Management Services (PMS) uses a series of cameras mounted on a survey vehicle, as shown in Figure 2.13, to collect road visual information, which can then be visually assessed by an inspector (Yeaman, 2004; PMS, 2007). The software system developed by PMS can assist the inspector in estimating sizes of features such as potholes and lane widths, based on a possessed calibrated grid on screen. GPS locations can also be collected during survey.

Figure 2.13: Vehicle with multiple digital cameras developed by PMS

Digital imaging in road condition surveys by BMCC

The Blue Mountains City Council's (BMCC) digital imaging system uses a battery of digital cameras mounted on a vehicle (Figure 2.14), to capture images of a road and its surroundings which are geo-referenced to GPS coordinates (Thomson & O'Brien, 2003). This allows a range of road features to be captured and linked to a road asset database.

Figure 2.14: Digital cameras mounted vehicle used by BMCC

Figure 2.15 shows the data capture window. The images captured provide road feature and road surface information which is visually assessed by an inspector as a desk-top exercise. The process is not automatic, with the key link being the visual assessment by the inspector.

Figure 2.15: Data capture window of the BMCC survey system

2.5 Towards Automated Assessment Systems

2.5.1 The Benefits of Automated Systems

The main issues that need to be considered in road condition assessment are the quality and consistency of condition data and the cost of a survey. Automated road survey systems have clear potential to be more repeatable and cost-effective than present survey methods (Berman & Buckley, 1998).

Table 2.4 summarises the trend of road condition assessment approaches. It shows that survey automation has powerful appeal on the grounds of both economics and consistency of results. Automated systems have the potential to provide direct savings in data collection and analysis costs. These benefits should lead to more effective asset management decision-making (Ferguson & Pratt, 2002).

	Assessment approach	Improvements / limitations
Past	• Manual inspection • Manual field assessment	• Labour-intensive • Time-consuming • Risky • Inconsistent and unreliable • Inaccurate
Present	• Surveys assisted by video or digital imaging systems • Manual assessment partly a desk-top exercise	• Safe • Labour-intensive • Time-consuming • More consistent / reliable • More accurate
Future	• Automated survey systems • Real-time automated assessment using artificial intelligence and image processing tools	• Cost-effective • Fast and safe • Consistent and reliable • Accurate

Table 2.4: Road condition assessment approaches

2.5.2 The Automation Conundrum

Given the obvious merits of survey automation, the key question is: why has the industry stopped short of developing more fully automated survey systems? The hardware and software components of an automated road feature survey system are available as off-the-shelf items, and a commercially available package that could handle a range of road features would likely be purchased by numerous transport authorities. Why hasn't such a package been produced?

Over the last decade, digital imagery techniques and computer hardware and software packages have continuously improved. The capability of a desktop computer's central processing unit has increased from 300 MHz to over 3 GHz within the last 8 or so years, easily able to handle real-time image grabbing and processing. Similarly, advanced software packages such as Matlab have evolved and matured, and can provide the necessary analysis tools.

Current technology is thus powerful enough to allow an automated system to carry out survey and condition assessment tasks in real time, providing rapid feedback about a road's condition. Real time data processing also avoids the need to store large data volumes, although this is less of a concern given today's data storage methods; also, storage of the raw data may be of benefit if future survey techniques seek to re-analyse the historic data as a performance cross-check.

Potential road survey software analysis tools include advanced image processing techniques, and artificial intelligence systems. These latter include neural networks, which can be trained to recognise features in images and/or assess their condition; and expert systems which mimic human thinking. It was recognised a decade ago that these technologies had the potential to carry out image analysis in real time, and that it would quickly become a race to develop dependable image analysis systems which could generate condition assessment automatically (Giummarra, 1995). The race appears to be on hold for the moment.

The conundrum is that in spite of the development and ready availability of a range of these technological tools, to date their usage has merely supported, but not replaced, the specialist inspector. Councils and asset managers still largely rely on manual inspection methods. The analysis work in particular remains a lengthy and tedious affair. It is still a desk-top exercise, in which an inspector is required to look at the road survey images or videos to assess the road condition. Road surveys are still prone to error and are time-consuming, especially when dealing with interstate rural highways.

Technology has brought some benefits of course. For example, it is now common to use one or more digital cameras mounted on a vehicle to capture images of a road and its surroundings, and to archive the data within user-friendly databases, referenced to GPS coordinates. Some examples of visual survey and condition assessment that involve digital imaging or semi-automated systems have been provided earlier in this chapter. These systems are clearly laudable steps towards survey automation, but they are application specific and stop short of full automation. As significant as these advances are, condition assessment based on images has still not yet been fully automated, or integrated with concurrent and complementary information gained from remote sensing devices. The images captured by these systems are not processed further by feature recognition and condition assessment software routines. Why not?

One possible answer might be the cost of investing in new technology and developing familiarity with the established processes. Although attempts have been made to automate visual surveys using high and low speed measurement equipment, these techniques have not yet been fully utilised or remain unavailable at economical costs. It has also been reported that the experience with these systems has been mixed (Narendranathan et al., 2001; Männistö et al., 2000). However, while this argument may have been valid in the 1990s, it is believed that today the benefits of developing a fully automated survey system would easily outweigh the investment costs.

2.5.3 Explaining the Conundrum

The author considered the failure to develop more fully automated survey systems and, in consultation with others, identified two possible barriers to system automation. One barrier is the large number of possible survey targets and the different survey procedures associated with each target, such as cracks versus line-marking. A second barrier to automation the complexity of the survey environment, which involves changing road alignments and roadside environments, and changing survey conditions such as weather and light levels. An automated system needs to be adaptable and flexible enough to cope with these issues.

An analogy is found in nature, which has faced a similar problem: the biological design of animal body structures. It is known that no single animal can fill the disparate ecological niches occupied by mice, sheep, tigers, elephants and giraffes. Similarly, the present state of engineering know-how is unable to provide a single visual survey system that can satisfy every application, such as automating the identification and evaluation of road features as disparate as pavement cracking, signage, and roadside vegetation, since the assessment processes for each of these features are different.

A human specialist is in fact such a "single system" that can satisfy every application under most survey environments, but one whose performance is extremely difficult to reproduce. This is why manual inspection remains the most common visual assessment method. Although manual methods have limitations and can be expensive, they are easy to apply and their results remain acceptable.

2.5.4 Solving the Conundrum: An Approach to Automating Surveys

Nature points the way forward, through biomimicry, whereby nature's approach to solving a problem guides the engineering solution (Benyus, 1997). Thus, considering nature's approach to the problem of developing different animals appropriate for different ecological niches, it is realised that the different animals listed above are all based on the very successful quadruped design, whose common design components include the quadruped skeleton, eyes, ears, and various internal organs. Such a modular design forms the basis for quickly producing an animal able to fit a specific ecological niche.

Therefore, in the case of automating road surveys, a possible approach is to seek a generic system design, not a do-all survey system. The semi-automated systems described in Section 2.4.3 are tailored for specific and different road features, but have common design components.

Instead of developing a single system that can partially satisfy every application, this research seeks to develop a generic design approach, with clear principles to guide the design's application to specific survey tasks, and in particular drawing on the lessons of biomimicry.

We can anticipate that one approach to commercialising the generic design would be to develop a toolbox of software routines and so forth, largely based on image processing and artificial intelligence techniques, with guidance on using the toolbox to follow a generic design approach. This is exactly the approach taken by a modern technical computing package like Matlab, which contains toolboxes for signal processing and other specialist applications.

The second major barrier to system automation, identified in the previous section, is the need for a survey system to maintain high performance under changing road context and environmental conditions, particularly important for surveys of long rural highways. This research examines possible ways to extend automated systems to adapt to such changing circumstances, and the resulting methodology is to develop survey systems in a two-step approach, as described in Chapters 3 and 4.

3.0 BASIC AUTOMATION TOOLS

3.1 Introduction

Chapter 2 found that cost-effective automated systems are necessary to produce consistent, reliable and accurate road condition assessment results in real time. This chapter reviews the various computer vision techniques that can be used to develop such systems. Computer vision is understood to be the host of techniques to acquire, process and analyse complex data from our environment. Vision processes ranging from image formation to measurements or feature recognition are therefore regarded as an integral process of computer vision (Jähne & Haußecker, 2000).

Computer vision can be divided into image acquisition, image processing and feature recognition. In road feature survey, image acquisition can be undertaken using a software-hardware interface, while image processing and feature recognition can be done using a combination of Artificial Intelligence (AI) and classical software tools.

AI methods have their origin in the 1960s (Negnevitsky, 2001) and, since the advent of computers, have become widely recognised as powerful and elegant tools suitable for many engineering applications. The basic tools are expert systems, neural networks, and genetic algorithms, associated with decision-making, pattern recognition, and optimisation applications respectively. This chapter examines image processing and AI methods. The AI focus is on neural networks and expert systems, as they are the most useful in feature evaluation and condition assessment when used in conjunction with image processing.

3.2 Hardware and Interfaces

The current desktop computer hardware systems and digital imaging technologies are advanced and powerful enough to carry out condition assessment tasks automatically, and in real time. For example, a dual processor Pentium 4 machine in 2007 has a processing speed of well over 3 GHz, with up to 4 GB of physical memory. The computer is easily capable of handling image-based processing and analysis tasks in real time, taking less than a second to analyse each image.

The current (2007) generation of digital cameras can produce up to 6 megapixels per image, with digital zoom available if need be. Digital video cameras are also available that enable high quality road surveys to be carried out. For example, a Sony model SY148 digital camcorder, integrated with noise reduction and image stabilisation systems, is able to minimise the effects of shaking and vibration (SharperImage, 2005).

For road survey applications, a video card is required to link feed to a computer from a video cassette recorder (VCR), a digital video disc (DVD) player, or a video camera. This allows specialist imaging software to grab survey images from these devices for assessment. Smart video cards, such as the Picolo card (ADLINK, 2004) or the Osprey card (ViewCast, 2004), are best suited for image capture and input to a computer. When used in conjunction with specialist software through a control interface, as shown in Figure 3.1, a video card can also be used to control a camera to perform specific operations, such as zooming or focusing on a particular object in the scene.

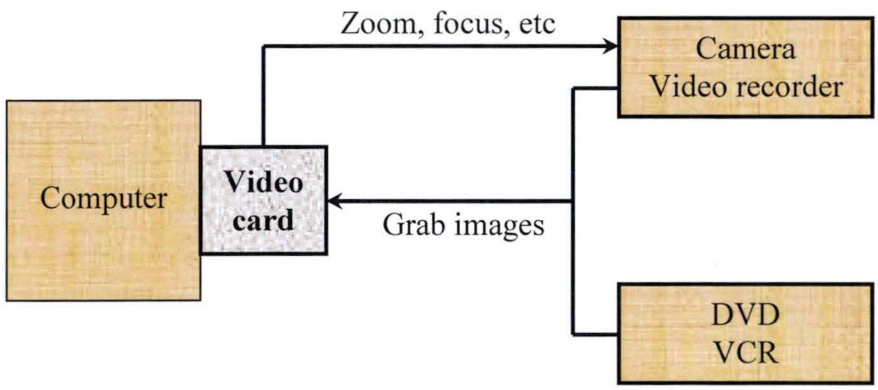


Figure 3.1: Hardware interfaces

Several protocols are now available to integrate systems that involve multiple applications. These protocols allow the development of interfaces between software systems, or software and hardware components. *ActiveX*, a commonly used high-level programming interface, is used for the present research. It is an object-oriented protocol, developed by Microsoft in the mid-1990s, and is built upon Microsoft's Component Object Model (IC, 2004; LEADTOOLS, 2004; MSDN, 2005).

One of the most popular uses for ActiveX controls is developing interactive content for Web applications, and to produce image animations and other multimedia effects, with user interaction. ActiveX is also the primary architecture for developing programmable software components for a variety of applications, ranging from software development tools to end-user productivity tools. Other protocols available for the development of programming interfaces are described in Appendix A.

3.3 Image Processing

3.3.1 Introduction

A significant difference between human and computer-based vision systems is the way in which images are acquired. The most common computer-based sensor is a standard digital camera, which uses a chip with an array of individual pixels. With technology which is now quite mature, it is possible to place arrays of more than 300,000 pixels (e.g. in an array of 750×400 pixels) in an area of less than 1 cm^2.

Image processing has been applied to equipment such as "smart" cameras for auto-focusing (Jähne & Haußecker, 2000). Other potential applications include image restoration, edge detection, topographical analysis, and disparity analysis (Starck et al., 1998). For example, image restoration has been used to deal with degradation of images due to the distortions of camera optics.

3.3.2 Basic Processing Tools

Recent years have seen the emergence of a number of sophisticated image processing methods as standard tools. Edge detection, morphological operations and data manipulation methods are of principal interest in road survey system development.

Edge detection

Edge detection is an image processing technique that identifies the edges of features (objects) in an image by looking for places where the pixel intensity changes rapidly. Two basic methods of edge detection are template matching and differential gradient analysis (Davis, 2005). Both these approaches aim to find where the intensity gradient magnitude is sufficiently large to be taken as a reliable indicator of the edge of an object, which is done with the aid of suitable convolution masks. Typical masks are the Roberts, Sobel and Prewitt masks, as described in Appendix B.

In the convolution of a mask with an image, the pixel values of the mask are multiplied by each pixel and its neighbours in a small region of the image, the region being the same size as the mask. The results are summed, and the output placed in the original pixel location. This is applied to all of the pixels in the image. In all cases, the original pixel values are used in the multiplication and addition, and the derived values are used to produce a new image (Russ, 2002). This technique is also used in other image enhancement processes, such as deblurring and image filtering.

Consider an $N \times M$ pixel image, A, and a 3×3 mask, B, as shown in Figure 3.2.

Image A

a_{11}	a_{12}	a_{13}	...	a_{1m}
a_{21}	a_{22}	a_{23}	...	a_{2m}
a_{31}	a_{32}	a_{33}	...	a_{3m}
...	...	...	...	...
a_{n1}	a_{n2}	a_{n3}	...	a_{nm}

Mask B

b_{11}	b_{12}	b_{13}
b_{21}	b_{22}	b_{23}
b_{31}	b_{32}	b_{33}

Intensity gradient G

	g_{22}			

Figure 3.2: Intensity gradient calculation for edge detection

The convolution of mask B with Image A at pixel location (x, y) is:

$$G = B(x,y) * A(x,y) = \iint A(\alpha,\beta)\cdot B(x-\alpha, y-\beta)\, d\alpha\, d\beta$$

$$\approx \frac{1}{MN}\sum_{\alpha=1}^{M}\sum_{\beta=1}^{N} A(\alpha,\beta)\cdot B(x-\alpha, y-\beta)$$

where α and β are dummy integer variables for the integration, the range of which is across the entire image, and the symbol " * " indicates convolution. G represents the output of the convolution process, in this case the intensity gradient matrix.

In Figure 3.2, the mask is slid over an area of the image, in this case the top left (3 × 3 pixels) portion of the image. The intensity gradient for pixel a_{22} is calculated as:

$$g_{22} = a_{11}b_{11} + a_{12}b_{12} + a_{13}b_{13} + a_{21}b_{21} + a_{22}b_{22} + a_{23}b_{23} + a_{31}b_{31} + a_{32}b_{32} + a_{33}b_{33}$$

The mask then shifts to the remaining image portion until the intensity gradients at all pixels (other than the boundary pixels) are calculated.

The differential gradient method normally requires two convolution masks highlighting the edges in the x and y directions respectively. The gradient of an intensity function I is therefore a 2-element vector defined as:

$$\bar{g} = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{bmatrix}$$

The magnitude of the intensity gradient at each pixel is: $g = \sqrt{g_x^2 + g_y^2}$

and the orientation of the edge is estimated using: $\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$

The template matching method requires up to 12 convolution masks capable of estimating the local component of intensity gradients in different directions. The edge gradient magnitude is approximated by:

$$g \approx \max(g_i \mid i = 1,\ldots,n)$$

where n is usually 8 (45° apart) or 12 (30° apart), and the corresponding direction is the edge orientation.

Edge detection has been used in many computer vision applications to identify the edges of objects in an image, so that the objects can be located within the image, and their properties such as area, perimeter, and shape can be measured (Parker, 1997). In road surveys, this is useful in identifying features such as road edges and line-marking, and in measuring road dimensions and properties, such as the size of a pothole, or the extension of a crack.

Many edge detection techniques have been developed based on the two basic methods described above. The Canny edge detector (Gonzalez et al., 2004) detects both strong edges, and weak edges that are connected to the strong edges. This process makes edges better connected, and is likely to detect the true weak edges when noise is presented. This well suits the application of identifying the boundaries of road features. Figure 3.3 shows the Canny edge detection method applied to an image of a road. The result is a binary image, with white pixels representing the edges of objects.

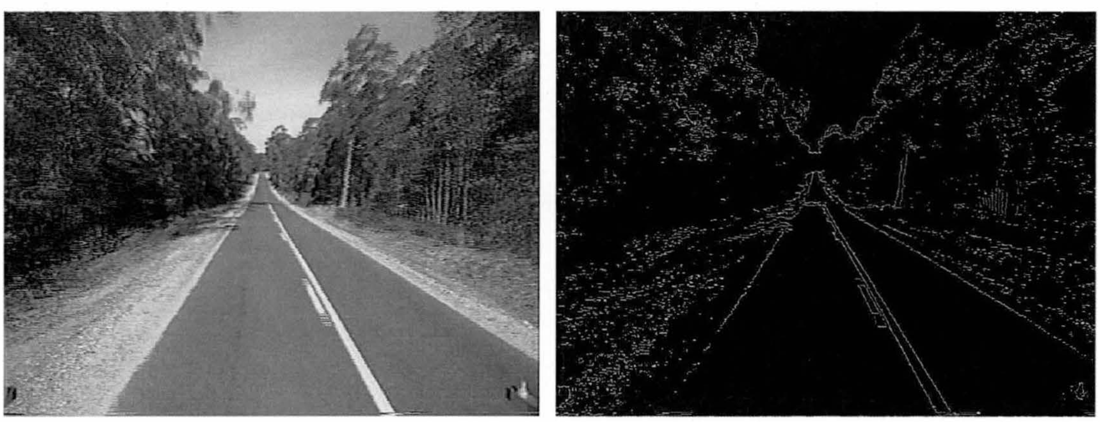


Figure 3.3: Edge detection

Two other edge detection methods were examined, namely the Laplace detector and the Zero-Crossings detector (Gonzalez et al., 2004), based upon the rate of change in intensity gradient (the second spatial derivative of intensity). The outcomes are similar to those of the Canny approach when applied to greyscale road images.

Morphological operations

Morphological operations are image processing techniques based on shapes. They are useful in performing several common image processing tasks. The value of each pixel in the output image is based on some form of comparison with the corresponding pixel in the input image with its neighbours. A morphological operation that is sensitive to a specific shape in an input image can be constructed by choosing the size and shape of its neighbourhood.

Two key morphological operations are dilation and erosion, which can be applied either to a greyscale image or to a binary image. A greyscale image is defined by a single array of pixel intensity values (usually 0-255), in contrast to a colour image which requires 3 arrays (Red, Green, Blue). For road survey images, dilation and erosion can be used in conjunction with edge detection to clarify an object's perimeter.

Consider first a *greyscale* image A and a neighbourhood C. Dilation and erosion of A by C can be carried out by:

$$A \oplus C = \max_{c \in C} A_c \qquad \text{dilation}$$

$$A \otimes C = \min_{c \in C} A_{-c} \qquad \text{erosion}$$

where A_c indicates a basic shift operation in the direction of element c of C, and A_{-c} indicates the reverse shift operation. When dealing with the greyscale images that are usually used for road survey analyses, the dilation shift operation replaces a given pixel value with the maximum value of all nearby (neighbourhood) pixels. The erosion shift operation replaces a given pixel value with the minimum value of all nearby (neighbourhood) pixels.

Consider next a *binary* image, for which the above operations simplify to (Davis, 2005):

$$A \oplus C = \bigcup_{c \in C} A_c \qquad \text{dilation}$$

$$A \otimes C = \bigcap_{c \in C} A_{-c} \qquad \text{erosion}$$

where A is now a binary image with pixel values of 0's (black) and 1's (white). For a binary image, dilation (erosion) adds (subtracts) pixels to better define the boundary of an object. The binary pixel values within the object are all set to 1 (white), and this enables subsequent analysis to be based only on those original greyscale pixel values corresponding to the white binary pixels.

Many other approaches to dilation and erosion have been developed, such as (Gonzalez et al., 2004; Morris, 2004; Laplante & Stoyenko, 1996):

$$A \oplus C = \{x \mid \hat{C}_x \cap A \neq \varnothing\} \qquad \text{dilation}$$

$$A \otimes C = \{x \mid C_x \cap A^c \neq \varnothing\} \qquad \text{erosion}$$

where $\varnothing$ is the null set, and

$\hat{C}$ is the reflection of C, $\quad \hat{C} = \{w \mid w = -c, \forall c \in C\}$

C_x is a translation of C to a pixel x, $\quad C_x = \{w \mid w = a + x, \forall a \in A\}$

A^c is the complement of A, $\quad A^c = \{w \mid w \notin A\}$

Dilation and erosion can be applied sequentially, leading to the morphological operations known as opening (an erosion followed by a dilation) and closing (a dilation followed by an erosion). These operations can be described by:

$$\begin{aligned} A \circ C &= (A \otimes C) \oplus C \\ &= \bigcup \{C_x \mid C_x \subseteq A\} \end{aligned} \qquad \text{opening of } A \text{ by } C$$

$$A \bullet C = (A \oplus C) \otimes C \qquad \text{closing of } A \text{ by } C$$

A morphological opening is often used to remove small objects and leave larger objects within an image. Figure 3.4 shows a morphological opening, based on using a disc 8 pixels in diameter (a "structuring element") as a mask, being applied to remove an arrow sign on the road that might otherwise confuse an automated condition assessment system.

In road feature evaluation, morphological operations can help to identify objects (features) within a road image. After an object is identified, a binary mask can be constructed to isolate the pixels that define the entire object, which facilitates passing

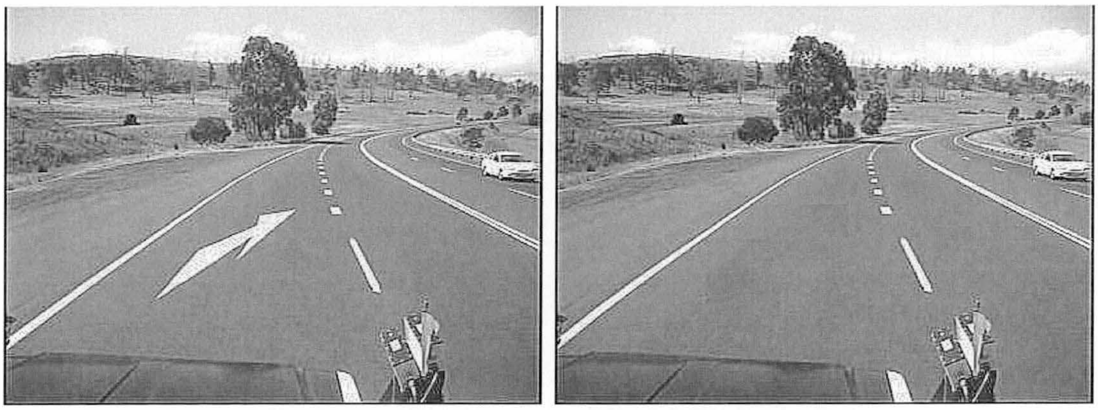


Figure 3.4: A morphological opening

only those pixels in the original image to the condition analysis procedures. Figure 3.5 demonstrates a binary mask being applied to isolate a portion of the line-marking within a road image.

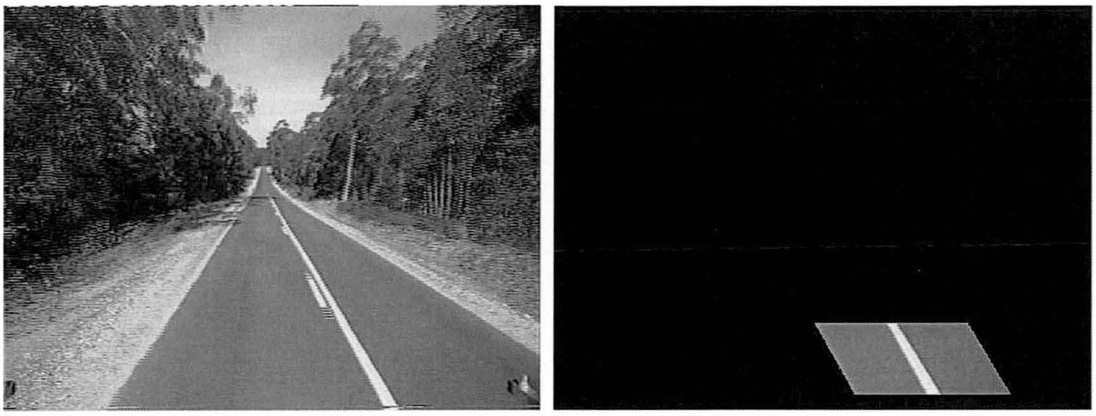


Figure 3.5: Binary masking

Manipulation methods

Basic image manipulation methods are:

- image resizing;
- image rotation; and
- image cropping.

Figure 3.6 demonstrates these methods being applied to the binary mask in Figure 3.5. Other manipulation methods include the spatial transformations of image translation, stretching, and shearing.

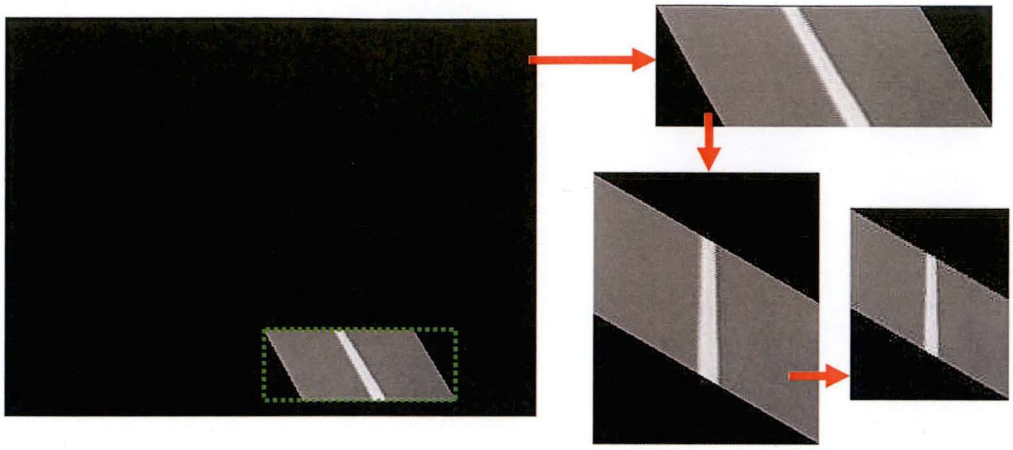


Figure 3.6: Image manipulation – cropping, rotating, and resizing

3.3.3 Image Enhancement: Noise Removal and Deblurring

Noise removal

Noise results from errors in the image acquisition process, producing pixel values that do not reflect the true intensities of the scene. There are several ways that noise can be introduced into an image, depending on how the image is created. In a digital image, the acquisition process which converts an optical image into a continuous electrical signal that is then sampled, is the primary source of noise through processes such as:

- fluctuations caused by natural phenomena, such as random electron fluctuations within resistive materials in sensor amplifiers or photodetectors, which add a random component to the intensity value of a given pixel;
- environmental conditions such as heat and temperature that affect electronic devices during image acquisition;
- mechanical vibration of a moving camera;
- malfunctioning pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitisation process; and
- electrical interference in the system.

Fortunately, noise is not much of a problem in road survey images acquired with modern equipment, as current camera technology does a good job of minimising image noise. However, if noise is introduced into an image due to the reasons listed above, or if survey videos taken some years ago are being analysed, several image processing techniques are available to enhance the image.

To effectively deal with noise, it is necessary to understand its distribution function. Some noise-inducing processes produce a random distribution of noise. Other processes produce noise spectra that can be described by Gaussian, uniform, or salt-and-pepper intensity distributions as follows (Starck et al., 1998; Umbaugh, 2005).

$$\eta_{Gaussian} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(g-m)^2}{2\sigma^2}}$$

where g is the noise intensity of a given pixel, m is the mean value of the noise intensity's Gaussian distribution, and σ is its standard deviation.

$$\eta_{uniform} = \begin{cases} \frac{1}{b-a} & \text{for} \quad a \le g \le b \\ 0 & \text{elsewhere} \end{cases}$$

$$\eta_{salt-and-pepper} = \begin{cases} \eta_a & \text{for} \quad g = a \quad \text{(pepper)} \\ \eta_b & \text{for} \quad g = b \quad \text{(salt)} \\ 0 & \text{otherwise} \end{cases}$$

In these expressions, the noise distribution functions, η, refer to the noise component of the pixel intensities in the image, which is not to be confused with the actual location of a given pixel.

Noise removal requires the use of a noise filter, the choice of which depends on the distribution of noise. There are several types of noise filters, such as mean, median and mode filters, and the Wiener filter. A mean filter generates each pixel of the filtered image as the average of the pixel values in an $N \times M$ neighborhood of the corresponding pixel in the noisy image. Examples are:

Arithmetic mean filter: $$\hat{A}(x,y)=\frac{1}{MN}\sum_{n_1,n_2\in W}B(n_1,n_2)$$

Geometric mean filter: $$\hat{A}(x,y)=\left[\prod_{n_1,n_2\in W}B(n_1,n_2)\right]^{\frac{1}{MN}}$$

Harmonic mean filter: $$\hat{A}(x,y)=\frac{MN}{\sum_{n_1,n_2\in W}\frac{1}{B(n_1,n_2)}}$$

where W denotes an $N \times M$ portion of the noisy image, B, centred at pixels (x, y); and $\hat{A}$ is the filtered image, which is an estimated clear image A.

Median and mode filtering are similar to mean filtering, but the value of each pixel in the filtered image is determined by the median or mode of the $N \times M$ neighborhood pixels in the noisy image, rather than the mean.

Another type of useful noise filter is the Wiener filter:

$$\hat{A}(x,y)=B(x,y)-\frac{v^2}{\sigma^2}[B(x,y)-\mu]$$

where v^2 is the noise variance, and μ and σ^2 are the local mean and variance respectively, represented by:

$$\mu=\frac{1}{MN}\sum_{n_1,n_2\in W}B(n_1,n_2) \qquad \text{(local mean)}$$

$$\sigma^2=\frac{1}{MN}\sum_{n_1,n_2\in W}B^2(n_1,n_2)-\mu^2 \qquad \text{(local variance)}$$

The Wiener filter works best when the noise is constant-power additive noise, such as Gaussian noise. Figure 3.7 shows a road image degraded by noise whose intensity distribution is Gaussian before and after the application of a Wiener filter to remove the noise. A Weiner filter can also be applied to an image adaptively, which is known as adaptive filtering.

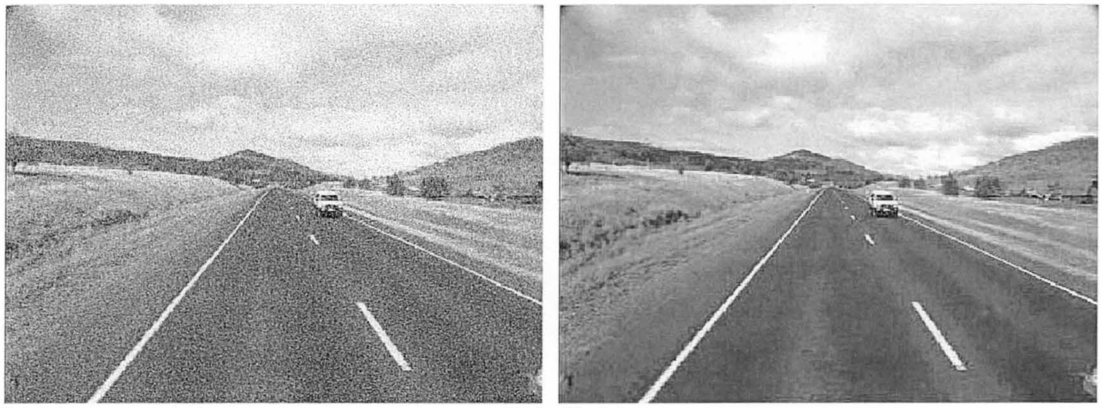


Figure 3.7: Noise removal

Image deblurring

Image deblurring is another useful image enhancement method and one perhaps more relevant to road surveys made with modern equipment. Blurring of an image can be caused by many factors, such as:

- movement during the image capture process, especially for road images captured from a moving survey vehicle;
- long exposure times; and
- out-of-focus optics.

A blurred or degraded image, B, subject to noise, η, can be approximately described by:

$$B \;=\; H(A)+\eta \;=\; H_s * A+\eta$$

where H is the distortion operator causing the blur effect, and A is the true unblurred image. The alternative form of the equation models the blurring as a convolution (*) of a point spread function, H_s, with the true image A.

In the frequency domain we have: $B_f = H_f A_f + \eta_f$

where the subscript f denotes a Fourier transform, a common operation in image processing (Gonzalez et al., 2004; Umbaugh, 2005). For a two-dimensional spatial function, such as an $N \times M$ pixel image, the discrete Fourier transform is:

$$F[A(x,y)] \;=\; A_f(u,v) \;=\; \sum_{x=1}^{M}\sum_{y=1}^{N} A(x,y)\cdot e^{-\imath 2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$$

and the inverse transform is:

$$F^{-1}[A_f(u,v)] \;=\; A(x,y) \;=\; \frac{1}{MN}\sum_{u=1}^{M}\sum_{v=1}^{N} A_f(u,v)\cdot e^{\imath 2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$$

where A_f is the Fourier transform of the image A; x and y are spatial variables (the pixel locations); and u and v are frequency variables.

As the degradation of the image is modelled as a convolution, the restoration process is referred to as deconvolution. This can be achieved by dividing the Fourier transform of the blur function to estimate the true image:

$$A_f \;=\; \frac{B_f}{H_f} - \frac{\eta_f}{H_f} \;=\; \hat{A}_f - \frac{\eta_f}{H_f}$$

In the absence of noise, η, the undegraded image can be found by taking the inverse Fourier transform, as:

$$\hat{A} = F^{-1}[\hat{A}_f]$$

If the noise is random, its Fourier transform, η_f, is unknown, and it is impossible to recover the true image by a method which relies on Fourier transforms. A common alternative method is the Wiener deconvolution, which has a long history as a practical method for achieving useful blur removal. The Wiener Filter can be represented in the frequency domain by (Gonzalez et al., 2004):

$$A_f \approx \hat{A}_f \;=\left(\frac{1}{H_f}\right)\left(\frac{|H_f|^2}{|H_f|^2 + \frac{|\eta_f|^2}{|A_f|^2}}\right)B_f \qquad \text{where} \quad |H_f|^2 = H_f^* H_f$$

which can be simplified to:

$$A_f \approx \hat{A}_f = \left(\frac{H_f^*}{\left|H_f\right|^2 + K} \right) B_f \qquad \text{where} \quad K = \frac{\left|\eta_f\right|^2}{\left|A_f\right|^2}$$

H_f^* is the complex conjugate of H_f, and K is the noise-to-signal power ratio, which depends on the statistical properties of the images and their relative noise contents. K is usually not known and so it is typically treated as an adjustable parameter that controls the tradeoff between image sharpening and noise.

Figure 3.8 shows a road image blurred by the movement of the survey vehicle. This motion blur is the most common type of blur effect in road survey images, and typically occurs during a survey with significant vibration. The image in Figure 3.8 has been deblurred by the author using Wiener filtering with a "Motion" point spread function, such that the appearance of the road features is enhanced. Many other deblurring techniques exist, as described by Chan & Shen (2005), Umbaugh (2005) and Gonzalez et al. (2004).

Figure 3.8: Deblurring using the Weiner filter

3.3.4 Applications of Image Processing to Road Surveys

Image processing can be used to detect road features within an image, such as cracks and defects, and line-marking and guideposts. When used in conjunction with artificial intelligence tools, notably neural networks, image processing helps a computer system to recognise patterns such as objects within images (e.g. guideposts and road signs), and vehicle registrations (Parker, 1997).

Image processing has many other potential applications to road and traffic management. Burrow et al. (2000, 2003) review U.K. research of digital image analysis methods to assess road marking. Chung & Shinozuka (2003) and Wang (2000) report on U.S. road survey systems that examine road surface distress with the aid of image processing. Australian road imaging systems are reviewed in Chapter 2, with notably successes being the method used by the SA DRT to measure road marking paint wear, and the *RoadCrack* system used by the NSW RTA to detect the type and severity of pavement cracking.

Another application of image processing is motion analysis, which may also have potential applications to road surveys. Motion analysis methods include the automatic recognition of certain objects within an image, ways to determine their locations, and tracking of those objects through a sequence of images (Jähne & Haußecker, 2000).

Image processing methods are powerful aids to road survey system automation. The present research aims to examine how these methods can best be incorporated into a generic survey system design, and to this end it is believed that such techniques are best employed to pre-process images for input to neural networks; and to provide assistance to neural networks in feature recognition tasks.

3.4 Expert Systems

Fuzzy logic was founded by Zadeh (1965). It is considered the foundation of fuzzy set theory, which is an extension of classical set theory. Fuzzy logic mathematics is ideal for handling vague, imprecise or uncertain data, and it can easily handle non-linear relationships (Nguyen & Walker, 2000; Mukaidono, 2001; Openshaw, 1997; Konar, 2000).

Expert systems are transparent decision-making tools, and a principal artificial intelligence method. An expert system consists of a set of rules prescribed by experts, which are evaluated using fuzzy logic. The rules use linguistic variables, which provide a means of "computing with words" that can improve computational power. They can provide insight into the links between the input and the target variables.

In decision-making problems, there are many situations in which expert rules offer a better approach to describing relationships between variables than classic approaches. They are well suited to the tasks of multi-criteria assessment and aggregation of information. There is no added complexity to using an expert rules approach, since the inputs are the same as those used by the corresponding classic decision-making method. Several expert system software packages are available, and Matlab and its fuzzy logic toolbox are used in this research.

Until the 1990s, expert system applications tended to focus on decision-making aspects of machines, and the word "fuzzy" became associated with "smart". Expert systems have now found applications in running washing machines, traffic lights, and a host of industrial machines, with examples discussed by Hushon (1990), Giarratano & Riley (1998), Chang (1997), Bien & Min (1995), Turban & Aronson (1998), and Yen et al. (1995). Expert systems have also been applied to the decision problem in auto-focus cameras to select the proper object to focus on, and also to image stabilisation in camcorders. More recently, expert systems have been applied as software tools in non-machine applications. For example, Ng (2002) used expert systems to assess the environmental performance of civil construction projects.

A rule can be defined as an IF-THEN structure that relates given information or facts in the "IF" part of the rule to some actions or conclusions in the "THEN" part of the rule. Two rules to determine how the condition of road features might affect road maintenance priority might be:

IF (*Patch* is *Less*) AND (*RoadEdge* is *Good*) THEN (*Priority* is *Low*)
IF (*Patch* is *Many*) OR (*RoadEdge* is *Cracked*) THEN (*Priority* is *High*)

In these rules, the input variables are *Patch* and *RoadEdge*, and the output variable is *Priority,* measured on whatever scales are convenient. These variables are "fuzzified" using "membership functions" such as *Less*, *Many*, *Good* and *Cracked.* Even without understanding the details of how expert rules are processed mathematically, it is clear that such rules can provide a natural way of thinking about problems (Berthold & Hand, 1999; Zimmermann, 1996; Baldwin, 1996).

A membership function is a curve that defines how each point in the input space is mapped to a membership degree that usually ranges from 0 to 1. Its functional shape (such as sigmoid, Gaussian, trapezoidal, or linear) is selected to be suitable from the point of view of simplicity, convenience, speed and efficiency (Tanaka, 1996; Kartalopoulos, 1996; Bandemer & Gottwald, 1995).

Figure 3.9 shows a step function and a sigmoid (S-shaped) function, either of which might be used to describe the concept of "adult". An advantage of expert systems is the ease with which non-linear membership functions can be used to model such concepts. In the left hand panel of Figure 3.9, an age of, say, 15 is defined as absolutely "not adult", while an age of, say, 25 is defined as absolutely "adult". Modelling the concept of adult with a sigmoid function, as is done in the right hand panel of Figure 3.9, allows these two ages each to be considered to be partly adult, and partly non-adult.

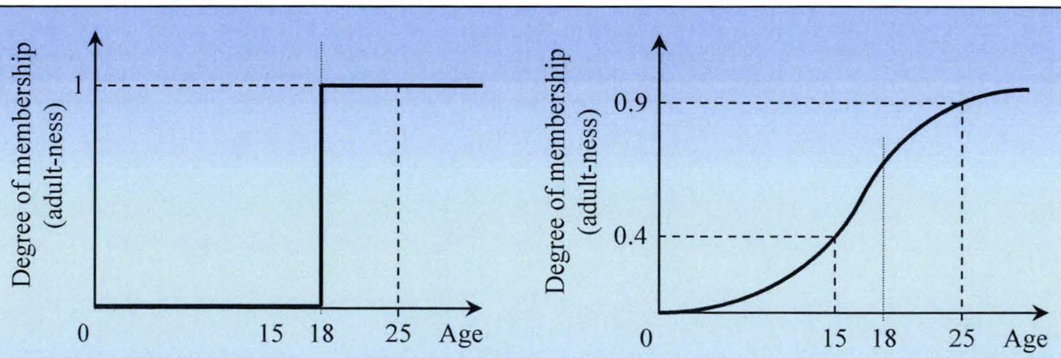


Figure 3.9: Membership functions used to fuzzify the concept of adult corresponds to legal definition (left) and biological definition (right)

For a given pair of input values (for example 45% of patching and 50 cm of edge break), the rules are evaluated using the mathematical operations "AND", "OR", and "NOT", which are usually represented by:

Fuzzy intersection or conjunction (AND) : $\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)]$

Fuzzy union or disjunction (OR) : $\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)]$

Fuzzy complement (NOT) : $\mu_A(x) = 1 - \mu_A(x)$

where μ denotes a membership function. The "THEN" operation is also usually applied using a minimum function. However, these are simply the most common choices for these operations. As discussed by Klir & Yuan (1995), the minimum and maximum functions are in fact part of a spectrum of fuzzy logic operations, although other choices are typically only applied to specialist situations and are not relevant to this research.

For additional insight into expert systems and fuzzy logic, the reader is referred to the case study in Appendix C on how road condition with consideration of context (such as horizontal alignment) might affect a decision on road safety.

3.5 Neural Networks

3.5.1 Introduction

Regression modelling is the classical approach to pattern recognition, which relies on minimising the sum-square error of some function that is fitted to data (Menard, 1995; Mendenhall & Sincich, 1996; Sen & Srivastava, 1990). Regression analysis works well in many applications, but is unable to handle problems involving recognition of patterns in 2-dimensional images, in which case a neural network modelling approach is necessary.

Humans have sophisticated in-built feature recognition systems, in which images are processed and patterns are recognised by the brain's biological neural network. Artificial neural networks are intended to mimic the way a brain carries out this work, and excellent neural network software packages (including that offered by Matlab) are now available.

Neural networks are used to perform complex functions in engineering applications involving pattern recognition, feature classification, and various prediction problems. For example, neural networks underpin character recognition systems (Cheng & Tarr, 2002), and voice recognition systems (Wu, 1994). In asset management, neural networks have been used to predict trends and patterns in asset failure rates, which can facilitate the modelling of investment options (WRC, 2004; Zhao et al., 1998).

Neural networks are composed of simple elements, known as "neurons", that operate in highly connected layers, as shown in Figure 3.10. The figure shows a typical neural network in which j input values ($x_1 \ldots x_j$) are directed to n neurons ($P_1 \ldots P_n$) in the input layer of the network. Optional layers of neurons between the input layer and the output layer of the network are termed hidden layers, and the network shown in Figure 3.10 has a single hidden layer with m neurons ($S_1 \ldots S_m$), and an output layer with k neurons ($T_1 \ldots T_k$), where k is the number of required output values.

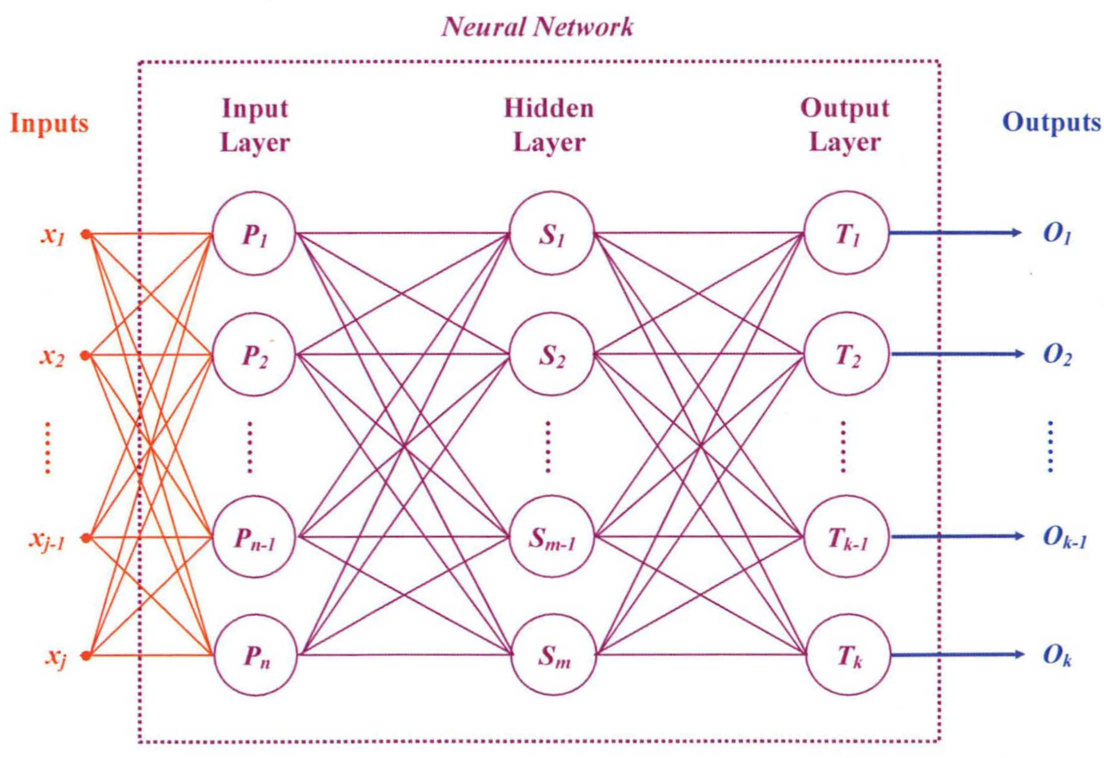


Figure 3.10: A typical three-layer neural network (Ng et al., 2003)

Each neuron is basically a mathematical function known as a transfer function which accepts an input and produces an output. Commonly used transfer functions include log-sigmoid, tangent, and pure-linear functions. Each neuron in the input layer accepts all the inputs, x_i, which here are the pixel intensity values. The input to the neuron's transfer function is the sum of the weighted inputs, with weight w_i applied to input x_i, together with a constant bias, b. The transfer function produces an output:

$$y = f\left[\sum_{i=1}^{J}(w_i x_i) + b\right]$$

Each neuron in the hidden layer and the output layer accepts as input all the outputs from the neurons in the previous layer, and processes them in a similar way: the outputs are weighted, summed, a bias is added, and the result is input to the neuron's transfer function.

A neural network is produced by adjusting the weights and biases of each neuron according to some training algorithm, as discussed in the next section. In many ways, a neural network is similar to a regression model, which is produced by adjusting a data fitting function's parameters in order to obtain a best fit. The major difference is that a regression model must know a priori the appropriate form of data fitting function, whereas a neural network will find the pattern in the data without this guidance.

A neural network is prepared for an application by using a set of baseline data to train it to recognise patterns in the data, such as image features. The baseline data contains both input data and the required outputs, and a training algorithm changes the weights and biases of all the neurons in the network until the desired output is achieved. This is usually done in "batch" mode, whereby a network is asked to predict the outputs for a batch of inputs, and then changes to the neurons are made with consideration of all the predictions.

Since a neural network's internal characteristics are hidden from the user, it is essentially a "black box" method. However, several methods based on neural network technology, such as adaptive or hybrid neural fuzzy systems, can be used to search numerical data for fuzzy rules. These methods can be used to suggest links between inputs and outputs, providing guidance regarding the nature of the pattern that the neural network has identified. These links can form the basis of rules for an expert system.

Neural networks are capable of learning, using experience to improve their performance. When exposed to a sufficient number of samples, neural networks can generalise to situations they have not previously encountered. They can also identify patterns that human experts fail to recognise (Negnevitsky, 2001). The design, training and use of neural networks requires a greater understanding of computer programming than is needed for expert systems. But neural networks can perform tasks that are beyond classical approaches to pattern recognition, so the effort is usually worthwhile.

A literature review suggests that neural network techniques have not yet found much usage in road surveys although, in conjunction with image processing methods, neural networks have clear potential to be used to evaluate road condition features. Lou et al. (2001) report on U.S. work to apply neural network models to forecast the short-term time variation of pavement surface cracking of highways, but no application of neural networks to Australian road management are known.

3.5.2 Applications of Neural Networks to Road Surveys

Pattern recognition

Figure 3.11 shows an image that consists of n ($n_R \times n_C$) pixels, with pixel values x_1 to x_n. Colour survey images can be converted into greyscale images by eliminating the hue and saturation information while retaining the intensity. This simplifies neural network analysis of situations in which features are to be identified whose principal characteristics are those of shape (such as a guidepost), not colour; or when the colour involved is white, such as the condition assessment of white lines. Most processing and analyses can be done in greyscale before reintroducing colour as ancillary information, if appropriate.

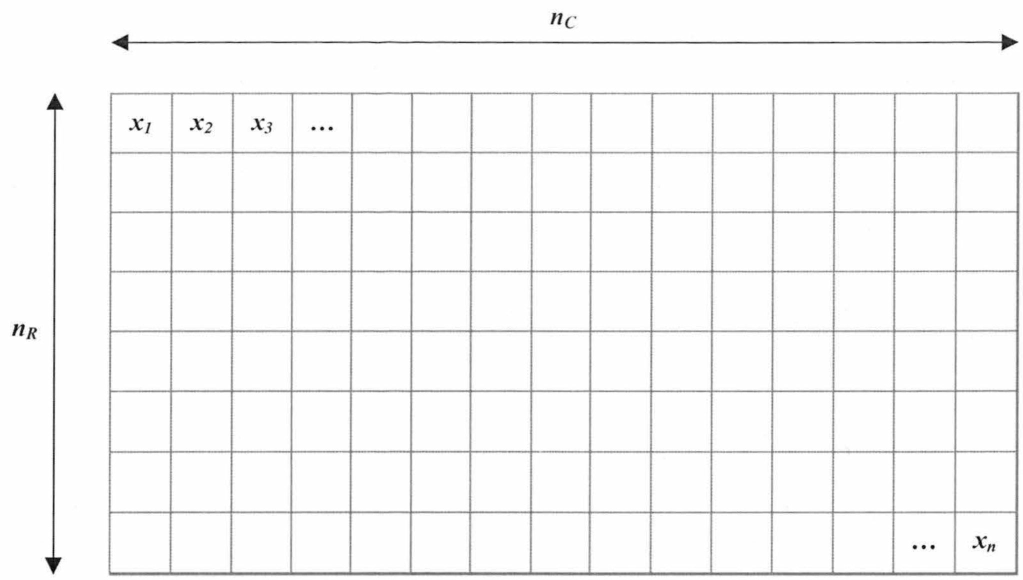
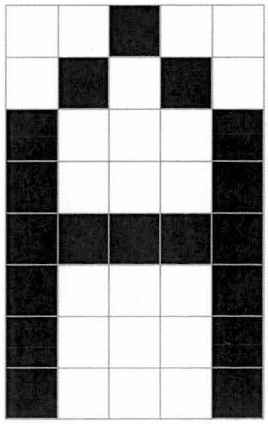


Figure 3.11: Image pixels

As noted, a pixel value represents the intensity of the image at the location of the pixel. In a greyscale image it ranges from 0 (dark) to 255 (bright). In a binary image, the pixel value is simply either 0 (black) or 1 (white). In a colour image, each pixel contains three values representing the relative intensities of red, blue and green.

In image analysis, such as a character recognition application, the input to a neural network is the entire set of pixel values of an image. For example, Figure 3.12 shows the binary values of pixels that form the character "A".



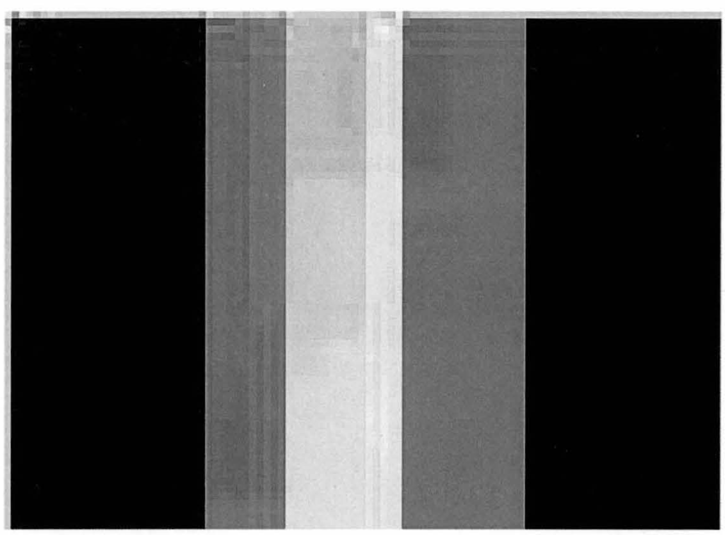
0	0	1	0	0
0	1	0	1	0
1	0	0	0	1
1	0	0	0	1
1	1	1	1	1
1	0	0	0	1
1	0	0	0	1
1	0	0	0	1

Figure 3.12: Pixels of character "A" and corresponding pixel values

The output of a neural network is tailored to the application to hand. In the case of character recognition, 26 step-function outputs might be defined, and an appropriately trained neural network presented with an image of the character "A", as shown in Figure 3.12, would respond by setting the first output to one, and all the other outputs to zero.

Road feature identification and condition assessment

Figure 3.13 shows the pixel values of the line-marking sub-image taken from Figure 3.6, resized to 13 × 18 pixels. These 13 × 18 = 234 pixel values are concatenated to produce a neural network input data set with 234 input values (x_1 to x_{234}).



18

13

0	0	0	0	0	114	123	195	192	231	110	120	123	0	0	0	0	0
0	0	0	0	0	114	123	195	189	228	107	117	123	0	0	0	0	0
0	0	0	0	0	114	123	195	190	230	108	119	123	0	0	0	0	0
0	0	0	0	0	114	123	195	193	233	112	122	123	0	0	0	0	0
0	0	0	0	0	115	123	205	210	235	124	128	127	2	0	0	0	0
0	0	0	0	0	115	123	205	214	234	119	121	124	0	0	0	0	0
0	0	0	0	0	115	123	205	213	233	117	119	120	0	0	0	0	0
0	0	0	0	0	115	123	205	209	231	118	121	118	0	0	0	0	0
0	0	0	0	0	114	114	212	222	235	123	123	123	0	0	0	0	0
0	0	0	0	0	111	117	220	227	238	126	125	123	0	0	0	0	0
0	0	0	0	0	108	116	223	227	237	123	121	123	0	0	0	0	0
0	0	0	0	0	107	114	221	225	234	119	117	123	0	0	0	0	0
0	0	0	0	0	120	123	222	227	232	117	119	123	1	0	1	0	0

Figure 3.13: Pixel values of line-marking sub-image

For a road line-marking condition assessment exercise, consider a neural network designed to produce 3 outputs (O_1 to O_3) that represent the line-marking condition as *Poor*, *Okay* or *Good*. In this case, the output layer needs to contain only k = 3 neurons (T_1 to T_3 in Figure 3.10). The three output neurons might have step transfer functions, with values only 0 or 1, or linear transfer functions with values between 0 and 1. Each output has a value ranging from 0 to 1, where 1 indicates that the corresponding condition is fully met, while 0 shows that it is not met at all. For example, an output [*Poor*, *Okay*, *Good*] = [0, 0, 1] means that the neural network has determined that the condition of the line-marking being analysed is good rather than okay or poor.

Neural network training

Neural networks trained for use in road survey applications typically require some 50 to 100 training images in order to make reliable feature recognition or condition assessments. A network architecture that is often satisfactory for these applications is a three-layer feed-forward network, with an input layer able to receive 200 or more inputs, and less than 100 neurons in the hidden layer, using either logarithmic sigmoid or tangent sigmoid transfer functions in the first two layers, and pure linear transfer functions in the output layer. *Feed-forward* refers to the one-way propagation of information from the input layer to the output layer.

Training a neural network is greatly facilitated by rescaling the input values to match the effective input range of the transfer functions. For example, a logarithmic sigmoid function requires its input values to be in the range -5 to 5 as shown in Figure 3.14 (left), and a tangent sigmoid function requires its input values to be in the range -3 to 3 as shown in Figure 3.14 (right).

Input values outside these ranges will produce outputs near 0 or 1 in the case of the logarithmic sigmoid function, and near -1 or 1 in the case of the tangent sigmoid function. The neural network training algorithm can, in theory, adjust the weights and biases associated with each neuron such that the input values are mapped to the effective input range of the transfer function. As explained in Section 3.5.1, the

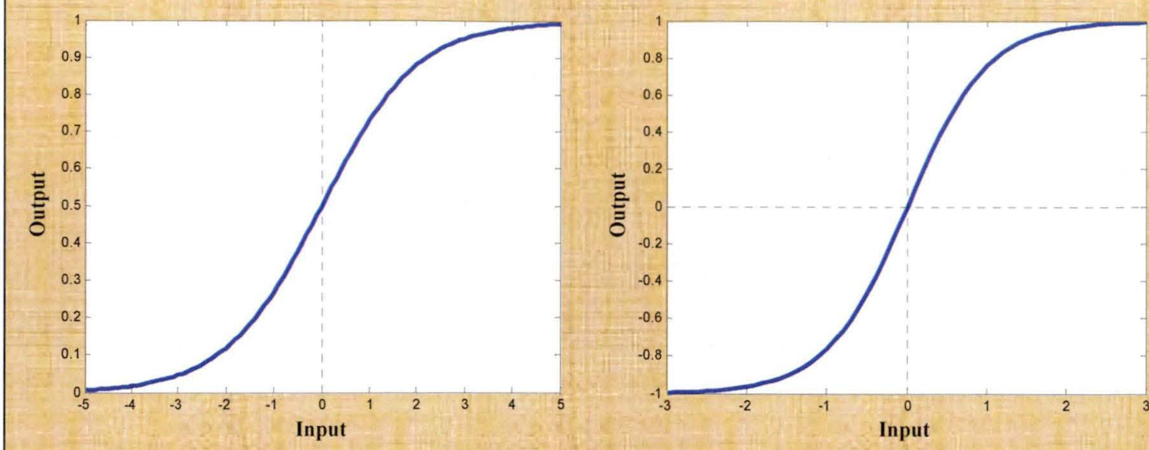


Figure 3.14: A logarithmic sigmoid function (left), and a tangent sigmoid function (right)

input to a transfer function is the sum of the weighted input values plus a bias, so the neural network can adjust the weights, w_i, applied to the inputs to incorporate a scaling factor, α, such that $w_i \rightarrow \alpha w_i$. Together with appropriate adjustment of the bias results in the inputs to the transfer function having the required range (±5 for a logarithmic sigmoid function).

However, experience shows that a priori rescaling of input values to roughly match the requirements of the transfer function facilitates the neural network training. When dealing with greyscale road images, the input to the neural network is a set of pixel greyscale intensity values ranging from 0 to 255, so a rescaling factor of about 0.02 is sufficient to place the inputs on the neural network training algorithm's radar.

Several training algorithms were examined by the author for this application, and the commonly used backpropagation training routine was found to be effective, using an error gradient descent technique, with momentum and an adaptive learning rate (Ng & Carter, 2003). An error gradient training approach means that the neuron weights and biases are adjusted to give the most rapid reduction in the sum-squared error between the neural network's actual output and its required output. The momentum parameter allows the neural network training to overcome localised minima in the sum-squared error surface, whereby small adjustments to the neuron weights and biases result in an increase in the sum-squared error, but slightly larger adjustments produce better assessments. The adaptive learning rate adjusts the training algorithm to take advantage of a relatively smooth sum-squared error surface (Demuth & Beale, 2003).

The degree to which a network has been successfully trained can be assessed from the network's performance when it is tested on a set of images which were *not* part of the training image set. A neural network is acceptable if it is able to make a strong decision, for example, in the above example if the output neuron transfer functions can produce an output value which varies continuously between 0 and 1, then an output set of [*Poor*, *Okay*, *Good*] = [0.3, 0.2, 0.8] denotes a good condition feature, and the value of 0.8 for the *Good* output shows that the neural network is fairly confident in this assessment. If the output is, say, [0.2, 0.4, 0.5], the neural network is again pronouncing the image to show a good condition feature, but this time it is less confident (and may be wrong) in its decision. In this case, this image can be added to the training set, and the network retrained until a more confident network performance is achieved.

The same approach is applied in the case of neural networks used for feature identification. In some instances, an automated system might mistake something for a specific feature. For example, a tree or sign post could be mistaken for a guidepost, or patching could be mistaken for a pothole. In these cases, neural networks can be trained to distinguish such features before further analysis.

The example presented previously for line-marking condition assessment is a simple illustration of how a neural network can be designed for road feature condition assessment. The neural network can be modified, for example, by extending the number of outputs to include, say, 5 conditions such as *Bad*, *Poor*, *Okay*, *Good* and *Excellent*, so that it is able to produce clearer decisions. Much depends on the quality of survey images available to feed the neural network. Alternatively, the neural network can be designed such that it only produces a single continuous output, say *Condition*, with a value ranging from 0 to 10, interpreted as bad (0-2), poor (2-4), okay (4-6), good (6-8) and excellent (8-10).

The size of the neural network can be increased by adding to the number of layers and/or to the number of neurons within each layer. This can be done in order to improve the network performance, especially for more complicated problems that involve more network outputs. However, it is important that a neural network's architecture is matched to the situation. A neural network with too few layers or neurons may not be able to handle a complex situation. However, too many layers and/or neurons may require an excessively long training and processing time, and the neural network may have trouble dealing with simple situations due to the phenomenon of overfitting, which is discussed below.

Road condition monitoring

A key finding in Chapter 2 is that one barrier to automation of road surveys and condition assessment is the inability of a survey system to maintain high performance under changing road context and survey environment. Automated systems need to adapt to such changing circumstances. To achieve this, the survey environment and road condition need to be monitored for change, and this task can again be done using neural networks. For example, a neural network can be trained to identify ambient light levels as *Bright*, *Normal* or *Dark*.

Overtraining of neural networks

Occasionally, a neural network might be overtrained. This results in the sum-square error of the training images being driven to a very small value, but when new images are presented to the network the error is large. This is because the network has not learned to generalise its analysis/operation to new situations.

This phenomenon is well known in polynomial fitting, whereby overfitting can occur when a higher order polynomial than necessary is used to fit the data, as shown in Figure 3.15. The blue dash line represents the function used to produce the data set with a random number to generate noise, and the red solid line denotes the output from a trained neural network. Clearly this network has overfitted the data and will not generalise well to new data. It fits the known data points very well, but fails to model the systematic aspect of the data. A good neural network should generalise well to new data.

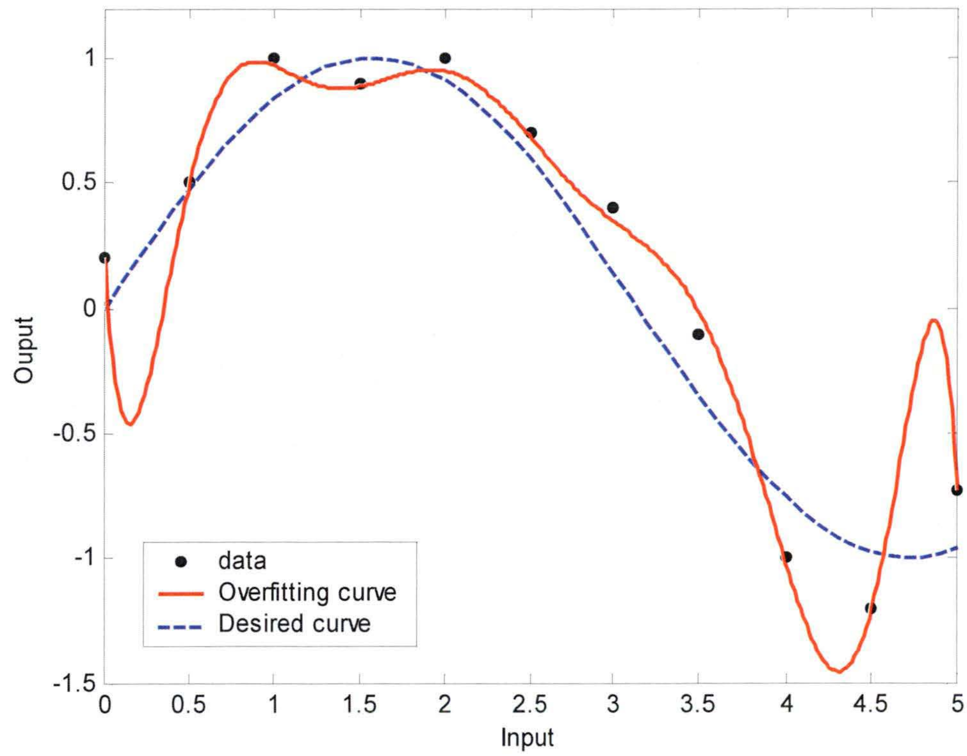


Figure 3.15: Overfitting of neural network

The problem of overfitting can be addressed by adding more images to the training data set, and retraining the neural network. However, if one is to make the most of a limited supply of data or images, then it is better to prevent overfitting in the first place. One rule-of-thumb is to select a network architecture that is just large enough to provide an adequate fit. The larger a network used, the more complex the functions the network can create. Therefore, reducing the size of a network can prevent overfitting, as a small enough network will not have enough power to overfit the data. By analogy a low order polynomial cannot vary wildly between the points it fits while a high order polynomial can. However, it is difficult to know beforehand how large a network should be for a specific application.

A more effective method for improving generalisation is early stopping, which requires a second set of images (apart from the training images), called validation images, to be passed to the training function. The sum-square error on the validation images is monitored during the training process. It will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the training image data, the error on the validation images data will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned.

3.6 Towards Automated Road Feature Surveys

This chapter has reviewed image processing techniques and artificial intelligence tools, which together with off-the-shelf hardware and interface systems have the potential to automate visual surveys of road features.

Image processing tools consist of basic operations such as edge detection, image manipulation and morphological operations; and image enhancement tools, notably noise removal and deblurring.

The principal artificial intelligence tools useful for road survey applications are expert systems and neural networks (the third major area of artificial intelligence techniques, genetic algorithms, are optimisation tools). Expert systems mimic the decision-making process of human experts. Neural networks are used for feature identification and condition assessment work, both of which are based on pattern recognition.

Artificial intelligence tools and image processing tools tend to complement each other, and therefore a road survey system should aim to combine these techniques. For example, image processing methods can help to isolate objects within an image, which avoids the need to train a neural network to do this job. Figure 3.16 outlines how these tools can assist the road management process.

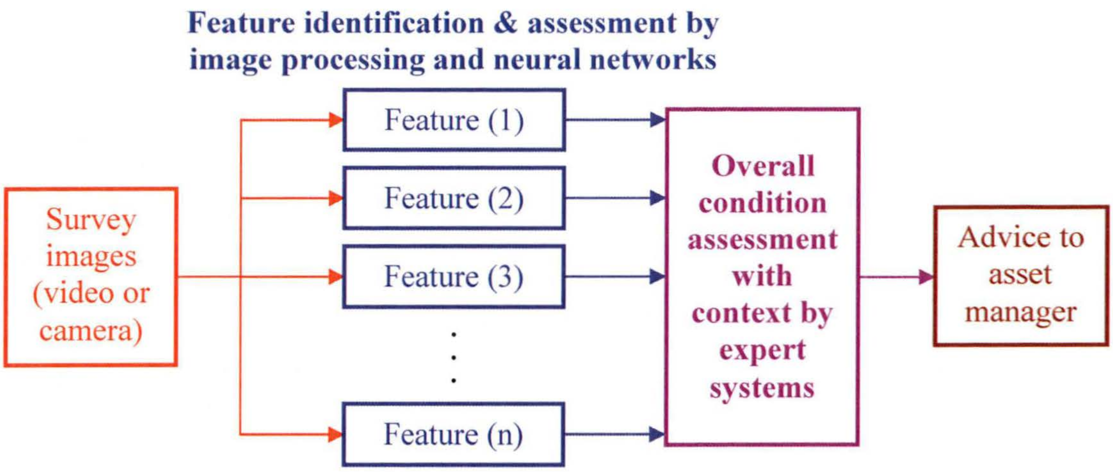


Figure 3.16: Artificial intelligence and image processing tools applied to road survey automation (Ng et al., 2006)

It is also noteworthy that the application of image processing and artificial intelligence tools to road surveys separates neatly into two stages.

For image processing, the first stage is the basic processing of road images, and the second stage is image enhancement to deal with issues such as noise and blurring. For artificial intelligence systems, the first stage is identification by neural networks of road features and assessment of their condition, and the second stage is the use of additional neural networks to monitor changing survey conditions. The use of expert systems is very relevant when road context is important.

This suggests that applying the generic survey design to produce a road survey system be carried out as a two-stage process:

1. Develop a *basic* system that establishes the fundamental aspects of a given survey assuming ideal survey conditions; and
2. Develop an *extended* system to handle complex and changing survey conditions.

The next chapter will present the generic survey design. Chapters 5 and 6 illustrate the application of this design to produce basic survey systems; and Chapter 7 demonstrates the development of an extended survey system.

4.0 A GENERIC SURVEY SYSTEM DESIGN

4.1 Automating Feature Surveys and Condition Assessments

The issues associated with the present approaches to road feature surveys were reviewed in Chapter 2. Visual inspections carried out manually are subjective and labour intensive. This has led to a surge of interest in the possibility of automating condition assessment work to complement traditional approaches. Artificial intelligence (AI) and image processing tools have clear potential to overcome the barriers to automation, and these tools were discussed in Chapter 3.

Automated systems to carry out road surveys have the potential to produce accurate, consistent and reliable results without involving excessive labour-costs, especially when dealing with long rural highways. Unfortunately, as pointed out in Chapter 2, a single fully automated survey system that can assess the condition of all road features does not exist, due to the number of possible survey targets and the changing nature of the road environment and survey conditions. Biomimicry suggests that possible solutions might be found by examining nature for clues.

Biomimicry studies nature's models and then imitates or takes inspiration from its designs and processes to solve human problems (Benyus, 1997; BFI, 2004). Several organisations around the world, notably the Rocky Mountain Institute, have put much effort into researching biomimicry (RMI, 2004). In some cases, biomimicry inspires approaches to solving problems which are easy to implement, an example being the use of artificial wetlands to treat wastewater. In other cases, it is clear that engineers still have much to learn from nature, an example being the way in which a spider produces a tough waterproof silk with high elasticity, using water at room temperature without high heat, inorganic chemicals, or pressure.

In the case of automating road feature surveys, nature suggests the seek to identify a generic system design that can be used to develop automated systems for specific applications. This suggestion is inspired by the quadruped design, notably the realisation that superficially quite different animals which have evolved to suit disparate ecological niches actually share a generic quadruped design. This chapter outlines a generic design approach inspired by biomimicry for preparing real-time image-based automated survey systems for rural highways.

4.2 Generic Design Overview

4.2.1 Design Components

Humans have evolved a highly sophisticated vision system for both image acquisition and analysis. As shown in Figure 4.1, it contains two eyes that view a scene and collect visual information from the scene as stereoscopic images. The image information is processed by the visual cortex, and by the biological neural networks that make up the brain, which constitute a powerful real-time processor. The brain compares images with an adaptive catalog (our memory), to identify and study changes in the scene, or to detect interesting targets in the images. If a target is identified, both eyes are rapidly slewed and focused on the target for detailed follow-up observations.

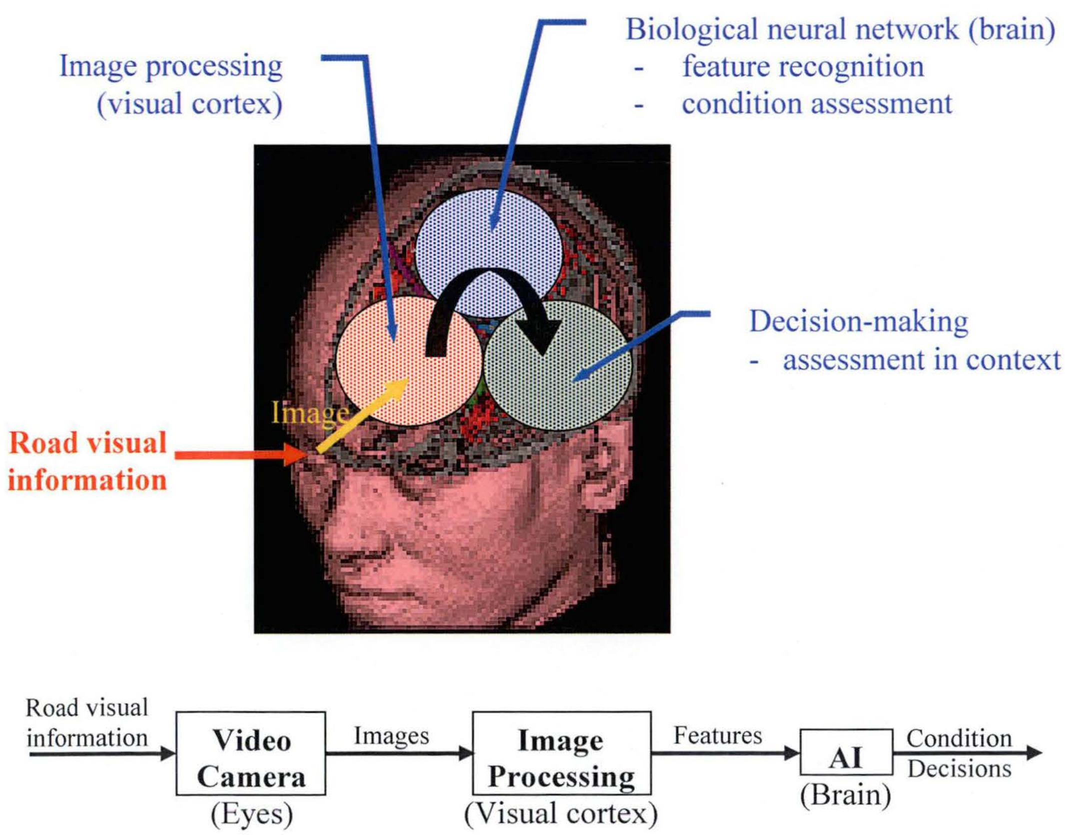


Figure 4.1: Biological (top) and artificial (bottom) vision systems

Figure 4.1 shows that a human visual survey system consists of three major components which must be mimicked by an artificial version of the system, namely an image acquisition component (the eyes), an image processing component (the brain's visual cortex), and an image analysis component (other parts of the brain). Figure 4.2 shows the artificial equivalent of these three principal components within the generic survey system design.

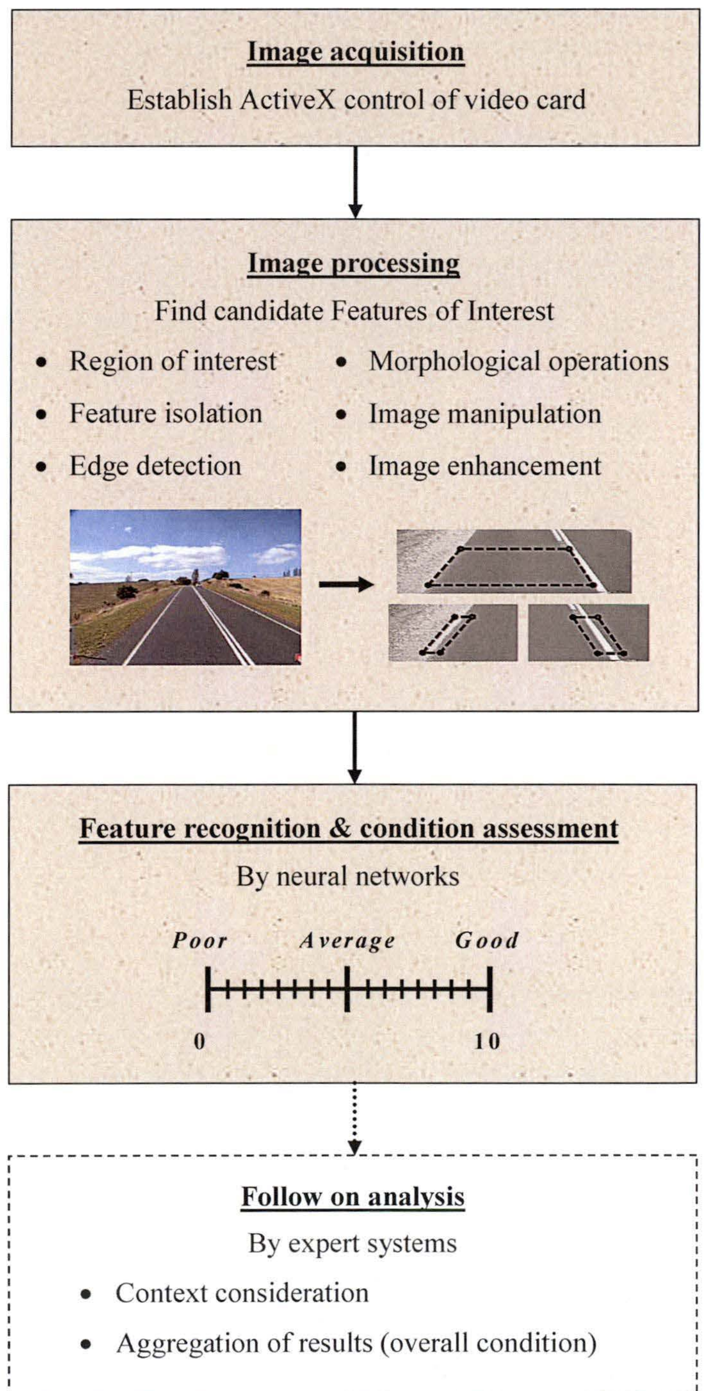


Figure 4.2: Generic survey system design components

In brief, road images are grabbed from video devices or a digital camera by a computer through a video card, and processed using the image processing tools described in Section 3.3 to identify candidate Features of Interest (FOIs) from a Region of Interest (ROI). Artificial neural networks then are used to recognise features within an image, such as line-marking, road edges, roadside vegetation, and guideposts, and to assess their condition automatically.

An ROI is that part of the image which contains the FOI. In nature, when a person is searching for, say, a child in a busy street, the person will tend to focus on the streetscape part of the field of vision, and ignore other parts of the image such as the sky and buildings. In other words, the streetscape is the ROI of the image in this instance. Within the ROI, the person focuses on identifying all small people, and ignores other objects such as large people and cars. In other words, the small people are the candidate FOIs.

The key goal of the first component of the generic survey system design is image acquisition, although more advanced future survey systems can be envisioned in which this system component is also responsible for adjusting image acquisition parameters by controlling the camera itself.

The key goal of the second major component of the generic survey system design is to identify candidate FOIs. In the case of road survey systems, the lesson from biomimicry is to focus on that part of the image (the ROI) that is likely to contain the feature of interest (the FOI), and ignore the rest of the image. For example, focus on the roadside for roadside vegetation assessment.

The third component of the generic survey system design focuses on the follow-on analysis of each candidate FOI (small people in the above example) to identify the correct FOI (here the child); and on examination of specific features (such as physiognomy, hair style, skin colour, clothing and so on). This task is primarily accomplished by neural networks.

A deliberate feature of the second and third components of the generic survey system design is that the task of identifying candidate FOIs is primarily carried out by image processing methods, while the analysis of each candidate FOI is primarily carried out by neural networks.

The reason for this is that image processing methods and neural networks have limitations when used in isolation. Neural networks struggle to identify candidate FOIs within an entire image, or even within a complex ROI, especially if the range of candidate FOIs is large. They work best when asked to carry out specific pattern recognition exercises, such as assessing whether a candidate FOI does indeed contain the FOI, or assessing the condition of an FOI. Image processing techniques tend to have complementary problems, in that they are well suited to the work of identifying candidate FOIs, but struggle to carry out pattern recognition tasks.

The separation of the second and third components of the generic survey system thus is based on recognition of the way in which image processing and neural network methods can complement each other. In a simplistic model of how the human brain works this can be viewed as equivalent to saying that the work of the visual cortex equates to image processing tasks, while higher level tasks of the brain equate to the use of neural networks.

4.2.2 Follow-on Analysis: The Role of Context

Follow-on analysis, if required, is the fourth component of the generic survey system, as shown in Figure 4.2. In general, this analysis can take many forms, but consideration of context is one requirement that is sufficiently common that it deserves highlighting. One of the main purposes of some road surveys is to generate condition data for decision-makers regarding road maintenance prioritisation, and consideration of the context associated with a road feature is an important aspect of this process.

Road context, such as horizontal alignment and roadside environment, is often linked to safety issues. Higher priority is given to maintaining the condition of high-risk road links, such as winding road sections, or road sections bordered by slopes. Such road sections are more prone to serious incidents when the condition of the road features is poor, such as unclear line-marking, missing guideposts or safety barriers, or poor surface condition. Therefore, an assessment system should be designed to take into account appropriate context factors, and should assign a lower condition score (or a higher maintenance priority) to problems on road links with higher risk.

The usual strategy for addressing context is to use a neural network to evaluate the context parameters associated with a survey, and then use an expert system as a post-processor to modify the significance of the condition assessment in light of its context. A case study illustrating this is provided in Chapter 6.

Another frequent task for follow-on analysis is that of aggregating individual road feature condition assessments into an overall assessment for a given road link (i.e. road section), and/or to aggregate overall assessments for different road links into a bulk condition index for the highway. The reason for such information aggregation is to provide at-a-glance condition assessment scores for the benefit of decision-makers or the public. Again expert systems are ideal tools for performing the task of information aggregation, and Appendix C presents a simple expert system that demonstrates the combination of line-marking and edge break condition assessment scores with consideration of context.

4.2.3 System Software

Several software packages are available to carry out image processing and analysis tasks. The Matlab software package (Version 6.5) was selected for use in this research because of its excellent image processing, neural network, and fuzzy logic toolboxes (MathWorks, 2002c). It provides a high-level technical computing platform and is particularly good at handling data arrays such as images. It also accepts an ActiveX interface command library that allows it to control a video card and integrate with other software systems. In brief, the Matlab toolboxes most used for road survey systems are as follows.

Image processing toolbox (4.0)

This toolbox supports a wide range of image processing operations, including spatial image transformations, morphological operations, filtering, image enhancement (such as deblurring), and Region of Interest operations (MathWorks, 2003a, 2003b).

Fuzzy logic toolbox (2.1.2)

This is a fairly mature toolbox which has not changed substantially in several years (MathWorks, 2002b). It provides tools for creating, editing and running fuzzy inference systems (i.e. expert systems).

Neural network toolbox (4.0.2)

This toolbox provides a suite of functions for developing and training neural networks (Demuth & Beale, 2003). It contains algorithms that can train a neural network in either batch mode or incremental mode. The early stopping function in combination with regularisation can improve the generalisation capability of a trained network.

Graphical user interfaces

Another useful feature of Matlab is its Graphical User Interface (GUI) development environment, which simplifies the software development process (MathWorks, 2002a). A user can lay out a GUI quickly and easily by dragging components, such as push buttons, pop-up menus, or axes, from the component palette into the layout area. Figure 4.3 shows an example of a GUI created by the author, for use in road feature identification.

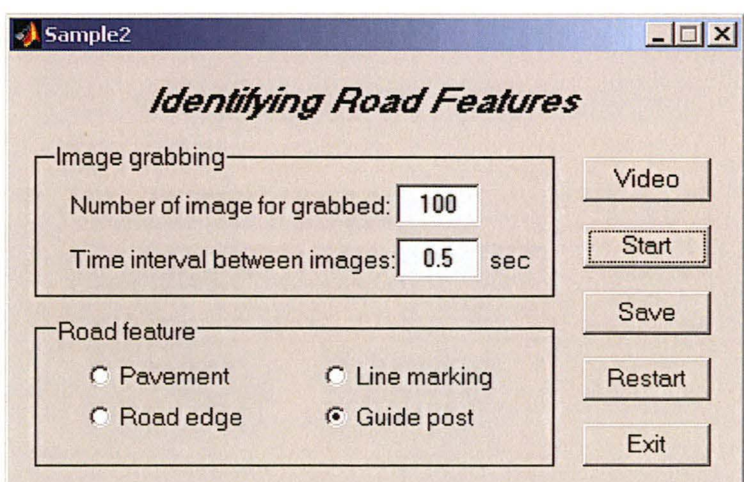


Figure 4.3: Graphical user interface used for road feature identification

4.2.4 System Hardware

This research was carried out using a 2.7 MHz Pentium-4 computer with 512 MB of physical memory, and a Windows XP operating system. A Picolo video card was chosen for image data acquisition. It is controlled by the imaging software package EasyGrab, developed by Euresys (Euresys, 2001) in its MultiCam 3.4 software series for Picolo (Figure 4.4). The EasyGrab library enables the card to carry out various imaging functions, or to control other connected hardware devices. For example, it can control a live-feed camera to zoom in on, or focus on, certain objects. As shown in Figure 4.5, the Picolo video card allows input to the computer to be acquired from a video cassette recorder via a BNC (Baby Neill-Concelman) link, or from a DVD player via an S-video digital link, or from live camera feed.

Figure 4.4: EasyGrab 3.4 developed by Euresys (Euresys, 2001)

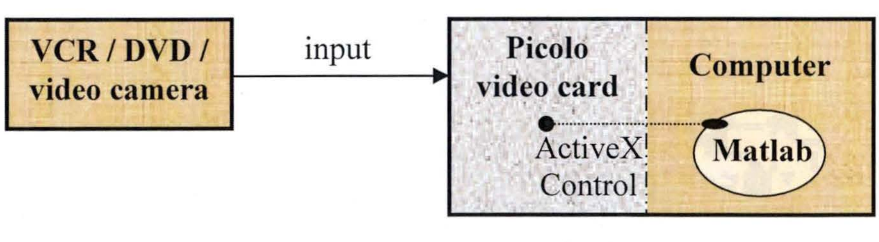


Figure 4.5: Video input via a video card

Matlab and the video card driver both recognise ActiveX commands, and an ActiveX control interface between Matlab and the video card allows a Matlab program to control the video card, and use it to grab images from survey videos recorded on video tapes, or DVDs, or from live camera feed.

4.3 Design Application Principles

4.3.1 Overview: Basic versus Extended Systems

It was noted in Chapter 3 that both image processing and artificial intelligence methods can be broken down into basic tools and extended tools. This has led to the idea of a two-stage road survey system development strategy: initial development of a *basic* survey system, followed by development of an *extended* survey system.

A *basic* survey system is one which is developed under ideal survey conditions. It focuses attention on the essential aspects of the survey system. It does not consider complex or changing survey conditions, as the software needed to address such issues can hide essential aspects of the survey system. A basic survey system requires only straightforward image manipulation and morphological operations, and the data used to develop the system (such as the neural network training images) should be of a fairly straight road whose roadside environment does not change significantly. In addition, the survey should be conducted at a moderate and constant speed in good weather conditions, preferably fine and cloudy with good diffuse ambient light (no shadows), and low wind (no movement of trees). This facilitates development of the fundamental aspects of the survey system.

An *extended* survey system is one in which the survey requirements are more complex, for example with changing road alignments and variable roadside environments; and/or survey conditions which encompass different light levels, occasional rain, and variable survey vehicle speed. Such a system requires additional image processing, possibly by advanced techniques such as noise removal and deblurring, as described in Section 3.3.3. Also, the neural networks that are trained to recognise features must either handle a wider range of conditions, or else the survey system must have supervisor software that identifies changing conditions, such as shadow effects, and adapts the survey accordingly.

Application of the 3-component generic road survey system design proposed in this thesis should be guided by the following principles:

(i) Apply biomimicry tools
(ii) Use a modular approach
(iii) Use a staged approach to analysis
(iv) Use ancillary information where available and appropriate
(v) Develop clear performance criteria

4.3.2 Apply Biomimicry Tools

Nature's generic quadruped design approach to evolving animals as different as a mouse and a giraffe to fit specific ecological niches has motivated the generic road survey design set out in this chapter. In addition, the *tools* used in such survey systems should include the biomimicry tools of artificial intelligence methods where appropriate.

The reason for this is that artificial intelligence methods can perform some survey tasks better than conventional tools. Neural networks can carry out feature identification or pattern recognition work involving images, and such work is difficult or impossible using regression analysis or other classical tools. Expert systems mimic the way in which people think about problems and make decisions, and provide a powerful and elegant way of considering road context (such as bends versus straight road) when assessing the condition of road features.

4.3.3 Use a Modular Approach

A useful biomimicry design application principle is to use a modular approach, which is to say use assessment tools in a modular way for different applications. This is a strong principle in any endeavour which involves repeated tasks, and again is a principle which can be seen in action in nature. For example, all quadrupeds have the same structure, which includes a head, four legs, and so on, but evolution changes the details of these features to suit animals for different ecological niches.

The modular approach principle in engineering is well appreciated. For example, most aircraft have a single pair of wings, an engine, a tail and so on. However, the details of these features are different for each type of aircraft, depending on the aircraft's usage and performance requirements.

There is clear potential to apply the modularity principle throughout road survey system applications, beyond the three basic design components (image acquisition, image processing, and feature recognition). Image acquisition using an ActiveX interface is itself a highly modular procedure, which is required by all survey systems. Considering image processing methods, the obvious modularity of these procedures is exactly why they are gathered together into a Matlab toolbox. The modularity can be further tailored to the specific application of road survey systems, especially more complex procedures such as noise removal and deblurring.

It is also important to ensure modular procedures are followed when using neural networks in road survey systems. The neural network architecture (number of neurons, number of layers, and type of transfer functions) and training methods (such as the number of training images, the training algorithm, and system test mode procedures) used for different survey systems are all quite similar.

4.3.4 Use a Staged Approach to Analysis

Another useful biomimicry principle is to use a staged approach to analysis. Consider, for example, the task of identifying roadside vegetation, which even an expert may find hard to do quickly. In the development of an automated system to perform this task, a single neural network charged with making a pronouncement on the type of roadside vegetation would need extensive training, and would still probably not be very reliable.

A staged approach inspired by the human (i.e. nature's) approach to carrying out the task would be to train one neural network to separate the vegetation into the broad categories of small plants, bushes and trees; and train additional neural networks to examine and classify these sub-classes of vegetation. This mimics the human expert who will automatically (subconsciously) tend to narrow down the range of vegetation by classifying it into several categories before further identifying each species.

The efficiency of using a staged approach to analysis can also be seen from several existing engineering applications. Carter et al. (2000) report on the development of a road traffic survey system in which an initial development approach that aimed to train a single neural network to directly recognise and categorise a wide spectrum of vehicles, ranging from B-double trucks to motorcycles, was quickly abandoned. They realised that a much better approach was to train one neural network to distinguish small, medium-sized and large vehicles; and train additional neural networks to distinguish different kinds of vehicles within each class (such as heavy vehicles consisting of buses, log trucks, B-doubles, and so on).

Another example is a river condition evaluation system developed for the Murray Darling Basin (MDBC, 2004), where expert systems are used in stages to aggregate river health indices. The first stage involved using expert systems to aggregate groups of individual indices into sub-indices (fish health, hydrology, and macro invertebrates), which were then aggregated into an overall river condition index by a different expert system.

4.3.5 Use Ancillary Information where Available and Appropriate

There is perhaps a tendency to restrict road survey procedures to the analysis of image intensity data only. But in nature, visual information is supported by ancillary information: concurrent taste, sound, touch, and smell.

Ancillary information has clear potential to assist some road feature identification and condition assessment tasks, especially when the survey system performance associated with image input data alone is poor. At present, if an inspector is unsure, say, about pavement cracking through visual inspection, he/she is likely to consider actual measurements of the depth of cracks, and use these data in conjunction with the visual data to support the assessment. Therefore, another biomimicry principle is to apply such ancillary information where available, and when appropriate, to support the image-based analysis procedures. Matlab can accept concurrent data on another input channel, so acquisition and consideration of ancillary data is straightforward.

Ancillary information such as surface roughness might be gathered by sensors on the survey vehicle, or it might be information digitised from a map, such as soil type. It might also originate from classical analysis of the visual data, ahead of passing the data to a neural network. One example is the use of best-fit curves to analyse the condition of road edges. The curve fit parameters can be passed to the neural network charged with assessing edge breaks, alongside the visual data.

Another example is consideration of the frequency distribution of pixel colours, which can significantly assist a neural network to identify features such as road signs or vegetation types. This information can be input to the neural network alongside the greyscale pixel intensity data. Figure 4.6 shows a histogram of the colours defining the image, which is also shown in Figure 4.6, containing a road sign and its immediate background. The horizontal axis is a colour index axis. A colour index defines a "colourmap" appropriate to information (e.g. temperature) which a user wishes to represent by colours. In this case, pixel colour information is being represented by the colour index, so the colour index is constructed from the red, green and blue intensity values for each pixel. In the histogram shown in Figure 4.6, the spectrum of pixel colours is mapped to a total of 115 colour index values.

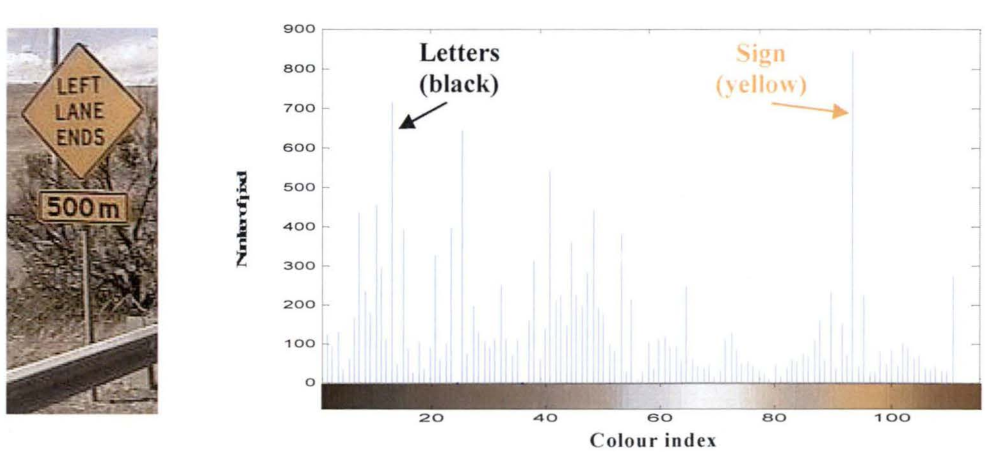


Figure 4.6: Pixel colour index histogram produced from an image containing a road sign

The histogram shows, unsurprisingly, that an image containing a road sign is characterised by a high frequency of yellow and black colour indices. This colour information can therefore be used to assist the work of a neural network.

4.3.6 Develop Clear Performance Criteria

Once a road survey system is developed, it must be tested and refined through application to a number of road sections, and under different survey conditions. A set of clear performance criteria needs to be established in order to examine the performance of the system. The obvious criteria to use are those set out in the manual inspection guidelines. However, it must be recognised that a road survey system may not be able to apply the exact criteria used by an inspector. For example, in the case study presented in Chapter 6, the camera orientation is such that assessing the condition of the white centreline-marking can only be done credibly using a *Good-Bad* scale, whereas a camera with a more downward orientation would enable better correspondence with the five-point scale (ROCOND, 1990) commonly used in manual surveys. A typical expectation is that an automated survey system should perform at least as well as the approximately 90% performance level of a well calibrated and proven manual assessment performance level.

4.4 Standard System Development Approach

4.4.1 Image Acquisition

Each road image consists of $n \times m$ pixels, with $n = 576$ rows and $m = 768$ columns at present, although these values can be varied to suit each survey application. The number of images to be grabbed and the time interval between each image grab depend on the feature being studied, and on the road condition. For example, if guideposts are being assessed, the image grab rate must be such that all guideposts are captured by the set of grabbed images, while avoiding a grab rate that is too high, such that the same guideposts appear in consecutive images.

Road images grabbed from a camera are colour images which consist of three sets of pixel values that represent the red, green and blue intensities. For simplicity, and to reduce the processing time and the complexity of the program, these colour images are converted to greyscale images with a single set of pixel intensity values ranging from 0 (black) to 255 (white). The idea behind this is that, since most road features and their condition can be identified "manually" by humans in greyscale, the assessment system should be able to process the data in the same way.

4.4.2 Image Processing

Road survey images need to be pre-processed ahead of a neural network analysis. The first step of image processing is to define an appropriate Region of Interest (ROI) to capture the Feature of Interest (FOI) given the camera perspective of the road. As road features are analysed individually, a different ROI is defined for each feature. All further processing is carried out within the ROI, instead of the entire image.

Identifying an ROI within an image may not be required if the camera is oriented and focused to directly look at the road feature to be surveyed (e.g. the roadside, if vegetation is being surveyed), in which case the whole image will become the ROI. However, when a single camera is used to survey different features, or when dealing with old (archived) survey footage that usually provides a wide-angle forward view of the road, which is the case in this research, then defining an ROI within the image is necessary. In addition, using a single camera to look at the entire road can sometimes produce a better survey, as consideration of context can be important, and too narrow an image is unable to provide information about horizontal alignment of the road, or the roadside environment.

Figure 4.7 shows the ROIs of two road features in the same image. The camera position and angle may vary slightly between images, so it is usually good practice to construct an ROI that is large enough to ensure capture of the FOI, while allowing over 75% of an image to be immediately discarded. Candidate FOIs are then extracted from the ROI. The number of FOIs within an ROI depends on the feature being surveyed. More than one FOI within an ROI is possible for features such as roadside vegetation or signs.

Figure 4.7: ROIs defined for guideposts (left) and centreline-marking (right)

Image processing techniques such as edge detection can detect the boundary of a feature as the place where there is a rapid intensity change. For example, by comparing the greyscale intensities between line-marking pixels ($\approx$200: bright) and pavement pixels ($\approx$80: dark), the boundary of the line-marking can be identified when there is an immediate change of about 120 units in intensity values between any two neighbouring pixels.

Figure 4.8 shows the candidate FOIs identified in the ROIs shown in Figure 4.7. Image processing is an exercise that has to be tailored for specific applications, and considerable time is often spent addressing exceptions to the rule. In the above example, for instance, a processing step that relies on the difference in intensity contrast between features may have a problem coping with wet versus dry weather, light versus shadow, or the effect of a vehicle's lights.

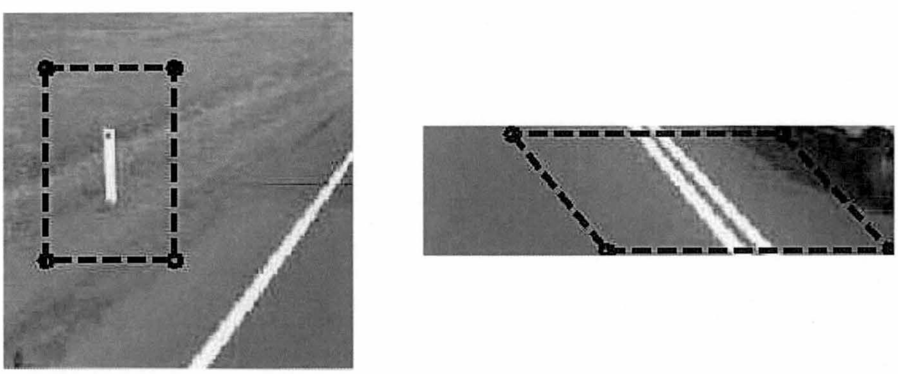


Figure 4.8: Candidate FOIs - guidepost (left) and centreline (right)

Figure 4.9 shows the result of using further processing, discussed in Chapters 5 and 6, to isolate the guidepost and the road line-marking FOI sub-images.

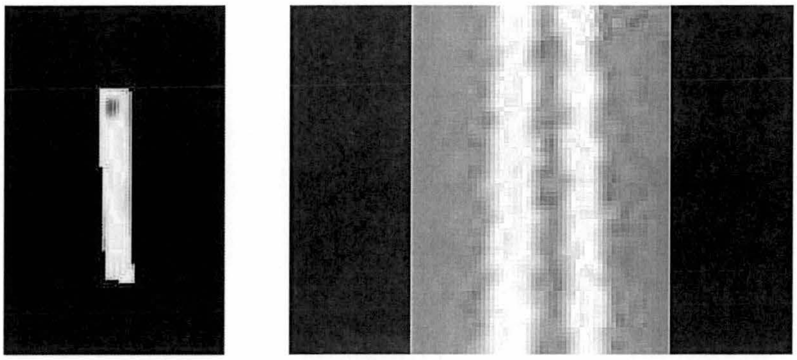


Figure 4.9: Isolation of the guidepost (left) and the centreline (right) FOIs, with a binary mask placed over the surroundings

4.4.3 Feature Identification and Condition Assessment

Standardise neural network inputs

Candidate FOI sub-images will have slightly different sizes. These sub-images must be converted to a standard size ahead of their input to a neural network, because a neural network requires all input records (here the number of pixels) to be the same size.

Image resizing is also required to ensure the size of an input image is not too large for a neural network to handle. For example, the original size of a line-marking sub-image is about 100×300 pixels, which equates to 30,000 input values. This would require a very large neural network, which poses problems in training the network, and increases the risk that the network will not always perform properly, the analogy being overfitting of a high order polynomial used to model a low order curve.

Resizing is an image processing technique that requires caution, especially resizing which reduces the image resolution. For example, Figure 4.10 shows three images of the same FOI. The left hand image shows the original $N \times M$ pixels. The middle image shows the FOI resized to 30%, which reduces the number of pixels to $0.3N \times 0.3M$. The right hand image shows the FOI resized to 10%, which reduces the number of pixels to $0.1N \times 0.1M$. The middle and right hand images thus contain less information about the FOI than the original image.

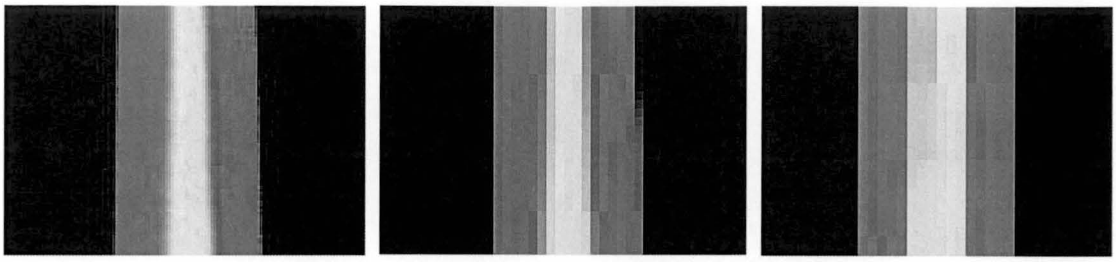


Figure 4.10: Resizing of a centreline sub-image
(left: original size; middle: 30% of original size; right: 10% of original size)

The survey system development task is thus to determine a standard FOI sub-image size that maintains the accuracy and reliability of the neural network analysis, a task that depends in part on the goal of the analysis:

- An analysis which simply aims to identify a feature can generally be accomplished using fairly low resolution images, and resizing an image to a standard size with fewer pixels than the original image may be acceptable.

- An analysis which aims to assess the condition of a feature generally requires good resolution images, and resizing an image to a standard size which contains more pixels than the original may be required (this does not, of course, increase the resolution *per se*, but ensures that little information is lost in the resizing operation).

Neural network development

The standard size candidate FOI sub-images are input into neural networks for feature identification. Each neural network is trained to identify a specific road feature. For features which require further classification, such as road signs, multiple neural networks should be used in a staged approach, as discussed in Section 4.3.4.

Experimentation shows that a 3-layer feed-forward neural network with up to 100 neurons with logarithmic sigmoid transfer functions within each input and hidden layer is generally adequate for road feature identification tasks, using about 50 training images (Ng et al., 2006). As discussed in Section 3.5.2, the neural network's training is facilitated by first multiplying the greyscale intensity values by a scaling factor of 0.02, to better match the effective range (~10) associated with using logarithmic sigmoid transfer functions.

Also as discussed in Section 3.5.2, many situations allow the specification of a neural network which contains two neurons in the output layer with pure-linear transfer functions, such that it can produce two outputs, *Yes* and *No*, each with a value between 0 and 1. If the candidate FOI sub-image indeed contains the feature of interest, the neural network will assign a higher value to *Yes* than to *No*. If not, it will assign a higher value to *No* than to *Yes*. The training image output values of [1, 0] and [0, 1] means that the extent to which the neural network is confident of its analysis is reflected in the actual values, with an output of [0.5, 0.5] corresponding to total uncertainty. Alternative neural networks can be developed that produce different outputs for feature classification, and sometimes are necessary. However, the simple *Yes-No* output pair is used where possible, to facilitate modularity.

Once a road feature is identified, another neural network is developed to assess the condition of the feature, if required. These neural networks use very similar architectures to those designed for feature identification, but with outputs appropriate to classification of the feature condition. For example, a typical set of outputs is [*Bad*, *Average*, *Good*], for which each variable has an output value range between 0 and 1, and the training output values are [1, 0 , 0], [0, 1, 0] and [0, 0, 1]. The output with the highest value denotes the result of the neural network's analysis of the feature's condition, and this set of outputs is appropriate for a condition classification exercise. Typically, about 50 images are required to train a neural network for successful condition assessment.

Another commonly used condition assessment measure is the continuous 0-10 scale, interpreted as poor (0-2), bad (2-4), average (4-6), good (6-8), and excellent (8-10). This can be implemented using a neural network with a single output neuron with a pure-linear transfer function. Other output designs are possible, but modularity of neural network development and application procedures argues for limiting the number of designs used in practice.

Neural network testing

The extent to which a neural network has been satisfactorily trained needs to be tested and refined in survey system test mode using a set of different input images, perhaps from different road sections. The neural network may mis-identify objects which were not well represented in the set of training images, or else may identify them correctly but with a low level of confidence. As described in the previous section, mid-range outputs of, say, [*Yes*, *No*] = [0.6, 0.4], mean that the neural network is not very certain of its analysis.

In system test mode, a user is prompted by a Graphical User Interface (GUI) to identify the new objects or feature condition manually. Figure 4.11 shows a GUI developed for feature identification in system test mode. A similar GUI can be developed for condition assessment. An image should only be added to the training set if the neural network was not very sure about the feature's classification, or got it wrong. The neural network is then retrained.

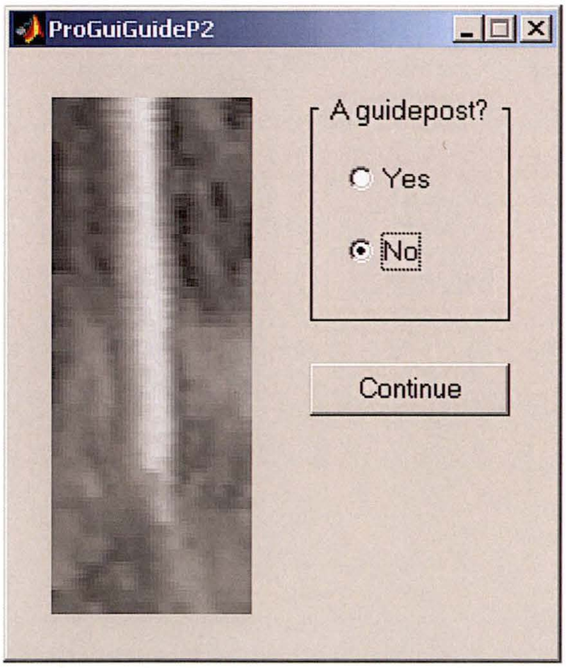


Figure 4.11: Identifying a feature manually

4.4.4 Follow-on Analysis

Once a road feature's condition assessment has been determined, a follow-on analysis may be required, and this is the fourth component of a basic survey system.

As discussed in Section 4.2.2, consideration of context can be separated into two tasks. First, the context associated with each FOI, image-by-image, must be assessed in an appropriate manner, which will usually necessitate the use of additional neural networks supported as need be by image processing methods. Second, the FOI condition assessment and the context assessment must be jointly considered in order to determine the importance of the condition assessment in the given context. This is a task ideally suited to an expert system. Section 3.4 and Appendix C together introduce expert system theory, with worked examples.

A typical expert system will thus need to accept at least two inputs: one or more FOI condition assessment scores (e.g. guidepost condition and line-marking condition) obtained from neural networks; and one or more context assessment scores (e.g. horizontal alignment and adjacent terrain type) for the road section being considered. The expert system output is the revised road feature condition assessment(s) in the given context. The expert system rules should revise the condition assessment scores downwards for risky road sections, especially if the road features are in poor physical condition, reflecting the requirement that such road sections need more attention.

Typical expert system rules that illustrate the consideration of context in a guidepost survey exercise might be:

IF (*Road* is *Straight*) AND (*Posts* are *LotsMissing*) THEN (*Condition* is *Poor*)
IF (*Road* is *Curved*) AND (*Posts* are *LotsMissing*) THEN (*Condition* is *Bad*)

Here, the input variables are *Posts*, representing the condition of guideposts, and *Road*, representing the road context (horizontal alignment in this example). The output variable *Condition* is the context-based condition assessment.

Also as noted in Section 4.2.2, a follow-on analysis may take the form of an aggregation exercise. This may require different weights to be assigned to different road features or road links, based on their relative importance, and again the role of context is also important. Consider, for example, an exercise to aggregate the condition assessments for pavement condition and line-marking. For a straight section of road, the road surface condition assessment would likely be assigned a higher weight than the line-marking condition assessment. However, for a section of winding road, the line-marking condition may be the more important road feature.

4.4.5 Performance Evaluation and System Extension

The performance of a basic survey system is examined based on the criteria targeted by the system design. A basic system is first operated under the ideal survey conditions that it is developed for, to confirm that good performance is achieved under such conditions. It is then applied to the range of actual survey conditions encountered over longer stretches of rural highway, which involve more complex conditions such as changing road alignments and changing roadside environment. If the basic system's performance is less than acceptable, which is expected, the factors that cause the reduction in performance need to be determined. For example, a basic system trained under fair weather conditions may not work as well under wet weather conditions.

Examining the basic survey system's limitations provides a basis for development of an extended survey system, using additional image processing techniques that may include noise removal and deblurring. Introducing a supervisory aspect to the survey system may also be required. This is discussed in detail in Chapter 7, and illustrated by a case study that includes a 50 km road survey.

4.5 Summary

This chapter has presented a generic design approach inspired by biomimicry to develop automated road feature survey and condition assessment systems intended for rural highway application.

The system design mimics the natural way in which human inspectors carry out road surveys and the condition assessment of road features. It uses a camera in lieu of human eyes, image processing methods to carry out the work done by a human visual cortex, and artificial intelligence tools (neural networks and expert systems) to carry out the tasks done by the human brain's cognitive areas. A Picolo video card is used to acquire survey system image input from a camera or survey video, and the Matlab computing platform is used to control the video card and to carry out the image processing and analysis work, due to its excellent image processing and artificial intelligence toolboxes.

The chapter also explores the idea that both image processing and pattern recognition can be separated into basic tools and extended tools. This leads to the premise that a survey system should have a two-stage development approach: first develop a basic survey system that performs well under good survey conditions, and subsequently develop an extended survey system to address the exigencies of longer, more challenging surveys.

The chapter sets out the generic design approach to developing a basic survey system, which establishes the fundamental aspects of the survey system. The design approach is supported by a set of design application principles, which are also largely inspired by biomimicry.

Case studies of basic survey systems are presented in Chapters 5 and 6, and the system extension methodology are presented in Chapter 7 together with the results of a longer (~50 km) survey.

The road feature condition deterioration cycle (as shown in Figure 2.4) can be monitored by conducting the same survey at regular (e.g. annual) intervals using such automated survey systems, and comparing results.

5.0 A BASIC GUIDEPOST COUNTING SURVEY SYSTEM

5.1 Introduction

Guideposts are uprights manufactured from various materials, standing in the shoulders alongside a highway, to delineate the road and to mark hazards. They are intended to be clearly visible during both the day and at night. Guideposts or their reflectors (adhesive delineators) are normally replaced when the reflectivity falls below specified levels, or more than 20% of the area of the reflector is either damaged or missing (DIER, 2004).

Guidepost counting is a significant part of guidepost assessment. It involves counting the total number of guideposts along a specific road link, and hence evaluating the number of missing posts. The traditional manual approach to guidepost counting involves an inspector carrying out the survey, either from a patrol vehicle, or from a recorded survey video. For a survey of a rural highway stretching hundreds of kilometers, this can be a tedious and error prone exercise. This chapter presents a case study in which a basic system is developed from the generic design approach outlined in Chapter 4, to count guideposts automatically, and in real time.

In brief, a basic system is developed under ideal survey conditions using short sections of road, so that the development work can focus on establishing the essential aspects of a survey system for the particular application. Ideal conditions are good weather conditions with sufficient (diffuse) sunlight, constant survey speed, straight road sections, and a simple roadside environment with not much roadside furniture. All good condition guideposts should have a clear reflection and easily identifiable appearance to the survey system under such conditions.

The system contains the usual three major components: image acquisition, image processing, and feature identification (note that the application of counting guideposts does not include assessing the physical condition of the guideposts). Classical image analysis is combined with a neural network for feature identification, and the basic system has a highly modular architecture.

5.2 System Description

5.2.1 System Startup and Image Acquisition

The Tasmanian State Government kindly provided archived road survey video footage for use in the case studies presented in this thesis. Each survey was recorded by a camera with a fixed orientation mounted on the top of a patrol vehicle.

Figure 5.1 shows the GUI developed to initialise the guidepost counting survey system. The GUI prompts the user to specify the required survey time and the rate of image grab.

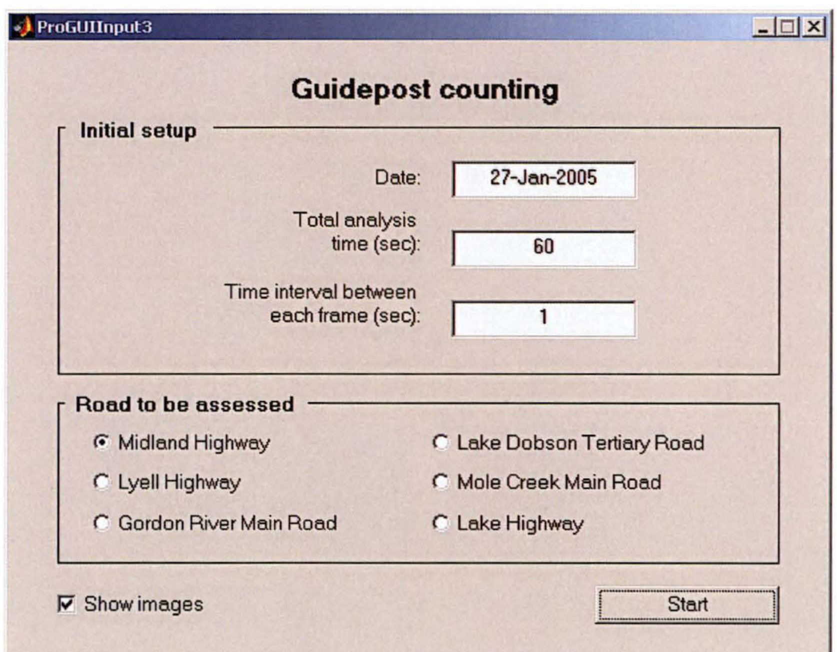


Figure 5.1: Guidepost survey system startup GUI

The "Show images" checkbox at the bottom left of the GUI enables the user to view all the images after their analysis. This is useful when the system is being operated in test mode, since it helps to determine where the system needs modifying, and the factors that cause problems.

Once the "Start" button is pushed, the survey is initiated by establishing the ActiveX interface between Matlab and the video card, and the survey feed is displayed on a monitor, as shown in Figure 5.2. The user instructs the system to start grabbing images, by pushing the "Grab" button on the top left corner. The system then starts to grab and analyse images at the specified rate, and runs for the specified survey period.

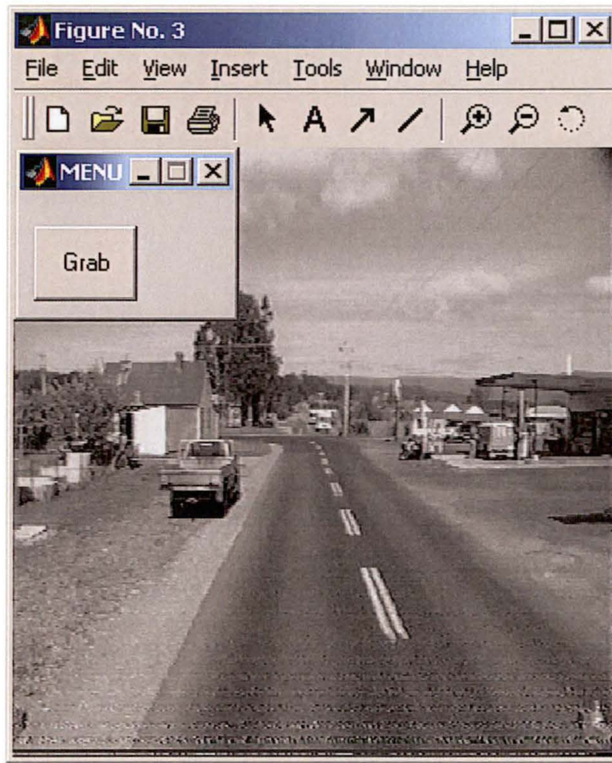


Figure 5.2: Survey about to start

5.2.2 Image Processing

Region of interest

Once an image is grabbed, it is converted into greyscale intensity format. A Region of Interest (ROI) appropriate to a guidepost survey is defined ahead of further processing. As noted above, the same patrol vehicle with a fixed survey camera orientation was used to obtain all the archived survey data considered by this thesis, enabling the guidepost ROI to be pre-defined for all these surveys. If the survey camera was not fixed (for example hand-held), a neural network could be trained to identify the boundary of the road as a reference for the guidepost ROI.

The key to a successful survey system is to ensure that the guidepost ROI is large enough and the image grab rate is sufficiently fast, to ensure capture of all guideposts as the patrol vehicle travels along the highway. If this balance is achieved, then distant guideposts that are not included in the ROI of a given image should be captured in the ROI of the next image, while a guidepost that is captured in the ROI of an image should not appear in the ROI of the next image.

A grab rate of one second (1 s) per image is appropriate for ideal highway survey conditions at a survey speed of about 80 km/h, since guideposts are typically set 60-150 m apart on straight road sections (AS 1742.2, 1994; DIER, 2005). The size of each survey image is 576×768 pixels, and the guidepost ROI was defined to be a 300×300 pixel region that covers the range of coordinates (1:300, 251:550), as shown in Figure 5.3.

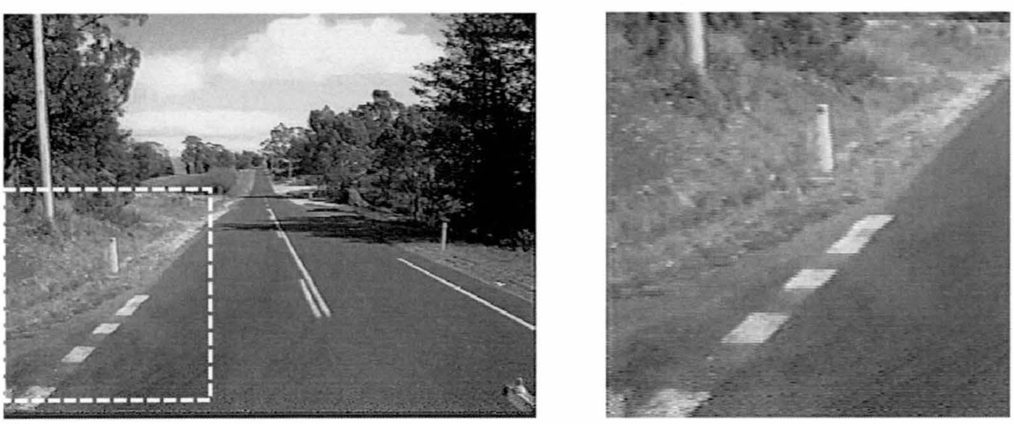


Figure 5.3: Region of interest for guideposts on left side of road

This ROI focuses the survey on the guideposts located on the left side of the road. A straightforward survey system extension would enable guideposts on both sides of the road to be surveyed, albeit subject to occasional visual interference from oncoming traffic.

The image processing procedures developed to carry out the task of identifying candidate Features of Interest (FOIs) within each ROI consist of four sequentially applied filtering processes: thresholding; preliminary object identification; large and small object removal; and consideration of object aspect ratios.

Filter 1: Thresholding

The greyscale ROI is converted to a black and white binary image, as shown in Figure 5.4, which highlights objects within the ROI that are brighter than their surroundings. These objects include guideposts, which are painted white. This conversion is done by the Matlab function *im2bw* using thresholding (MathWorks, 2003b), which changes those pixels with an intensity greater than a specific threshold into 1's (white), and the rest into 0's (black).

Figure 5.4: ROI is converted into a binary image

The threshold is a normalised greyscale value between 0 and 1 which can be specified as a constant for some surveys. From trials, a threshold of 0.75 ($\approx$192 on a 0-255 intensity scale) is suitable for distinguishing guideposts under ideal survey conditions: the intensity of most other objects within the ROI, including the pavement, is usually less than this value. These other objects are filtered out by the thresholding operation.

If light conditions are changing during the survey, thresholding using a fixed value does not always work. In this case, a supervisory neural network can be used to select an appropriate threshold for the current condition. This will be discussed in Chapter 7, when the basic system is extended to deal with changing environments.

Filter 2: Preliminary object identification

The second filter consists of two morphological operations (see Section 3.3.2; and MathWorks, 2003b). First, a morphological closing, using the structural element "line" with a length of 5 units and an angle of 90° from the horizontal, is applied to the binary ROI to connect all pixels associated with each object in the ROI. Next, a morphological opening, using a structural element "disk" with a diameter of 2 units, is applied to the resulting binary ROI to remove objects that are far too small to be guideposts. Figure 5.5 shows the resulting binary ROI.

Figure 5.5: Morphological operations applied to the binary ROI in Figure 5.4

Filter 3: Large and small object removal

Boundary pixels of objects in the binary image are obtained using the Matlab function *bwboundaries*. A boundary pixel is a white pixel that is connected to one or more black pixels. Figure 5.6 shows the boundaries of the remaining objects in Figure 5.5. The *bwboundaries* function can trace the exterior boundary of objects, as well as boundaries of holes inside these objects.

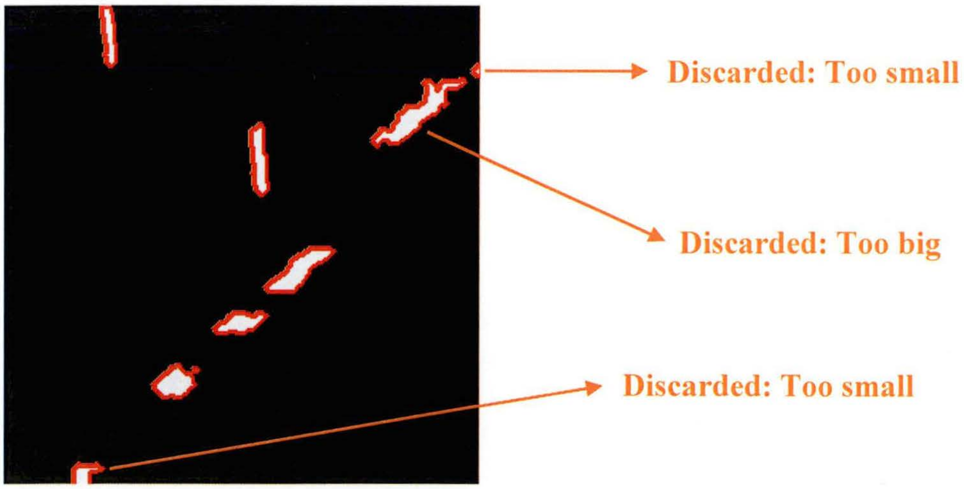


Figure 5.6: Boundary tracing on binary image in Figure 5.5

The size of an object within each boundary can be calculated in terms of the number of pixels. As the size of a guidepost is usually between 50 and 450 pixels, depending on its distance from the camera, a third filtering process can be applied to discard those objects that are either too large or too small to be a guidepost, as shown in Figure 5.6.

Filter 4: Consideration of object aspect ratio

The fourth filtering process considers the aspect (i.e. height to width) ratios of the remaining objects in the ROI, as shown in Figure 5.7, where the original image is reintroduced. Each remaining object's boundary is approximated by a rectangle that encloses its entire boundary, and its aspect ratio is calculated. The aspect ratio of a guidepost is greater than 2.5, and this criterion enables objects such as the white edge line in Figure 5.7 to be discarded as candidate guidepost objects.

Figure 5.7: Height to width ratio of objects

Figure 5.8 shows the two remaining candidate FOIs, after rejection of the white road edge line objects.

Figure 5.8: Output from image processing: candidate FOIs

In Figure 5.8, the two remaining candidate FOIs have similar physical properties (size, shape and intensity) to a guidepost, but may be objects such as telegraph poles, sign posts or traffic lights. While image processing techniques cannot easily distinguish guideposts from these objects, a neural network can do so.

5.2.3 Feature Identification

The first step of the feature identification exercise is to crop the sub-images of the two candidate FOIs in Figure 5.8 from the original image. Each FOI boundary is extended by 20 pixels on each side to ensure that the object is fully included in the sub-image, together with some background information which may help the neural network to identify the object. Figure 5.9 shows the two sub-images resized into "standard" 128 × 50 pixel images ahead of input into the neural network, since a neural network requires all input images to be the same size.

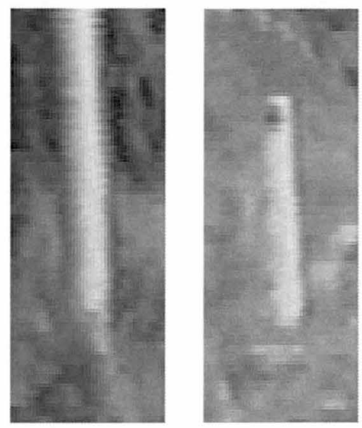


Figure 5.9: Resized sub-images, ready for input to a neural network

A 3-layer feed-forward neural network was developed to determine whether or not a candidate FOI contained in an input sub-image is indeed a guidepost. The neural network contains 100 neurons with log-sigmoid transfer functions in both the input layer and the hidden layer, and it accepts 6,400 input values (128 × 50 pixels). In addition, as discussed in Section 4.4.3, the pixel values are rescaled into the effective input range (about 10) of a log-sigmoid transfer function.

The network contains two output layer neurons, with pure-linear transfer functions, associated with two outputs, *Yes* and *No*. It is trained to produce [*Yes*, *No*] = [1, 0] if the input sub-image contains a guidepost, and [*Yes*, *No*] = [0, 1] if the input sub-image does not contain a guidepost (i.e. a different object). This effectively constrains the output of the pure-linear transfer functions to the approximate range of 0 to 1. Figure 5.10 shows typical outputs from the neural network.

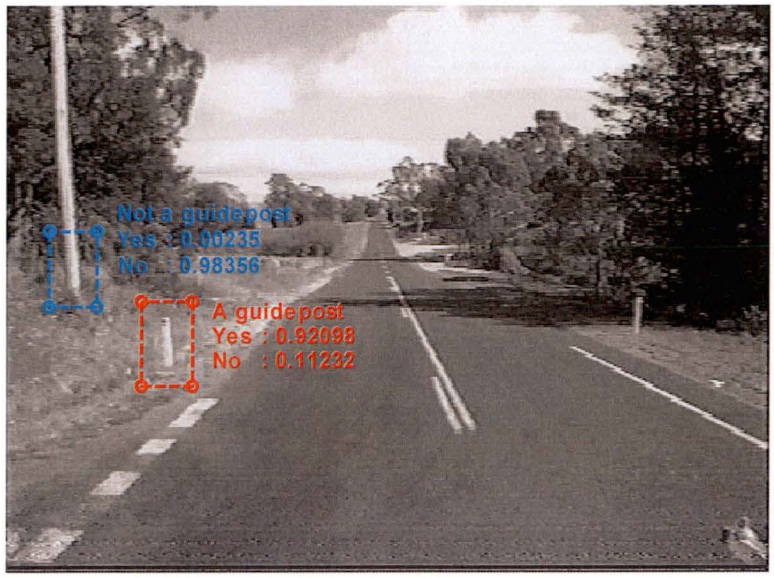


Figure 5.10: Output from the basic system

In Figure 5.10, a value of *Yes* greater than *No* means the network recognises that the input image contains a guidepost. The neural network was trained using 30 sample images containing guideposts or other objects. More training images can be added during the survey system test mode, when new objects are captured that the neural network either incorrectly identifies, or identifies correctly but with a low confidence level (Section 4.4.3).

5.2.4 Image Repetition Issue

Figure 5.11 shows an image repetition incident, which was observed to occasionally occur during image grabbing. The problem is believed to be a data acquisition error by the video card, as it happens for both input from the VCR and camera feed. Although handling this problem is not a fundamental aspect of a road survey system, in this instance it was treated as fundamental, since the research budget did not allow purchase of an alternative video card.

As shown in Figure 5.11, the data acquisition problem results in objects in an image being duplicated. This is not a blurred image, and the problem cannot be addressed using deblurring methods. However, a minor extension to the image processing operations described in Section 5.2.2 was found to address this issue successfully.

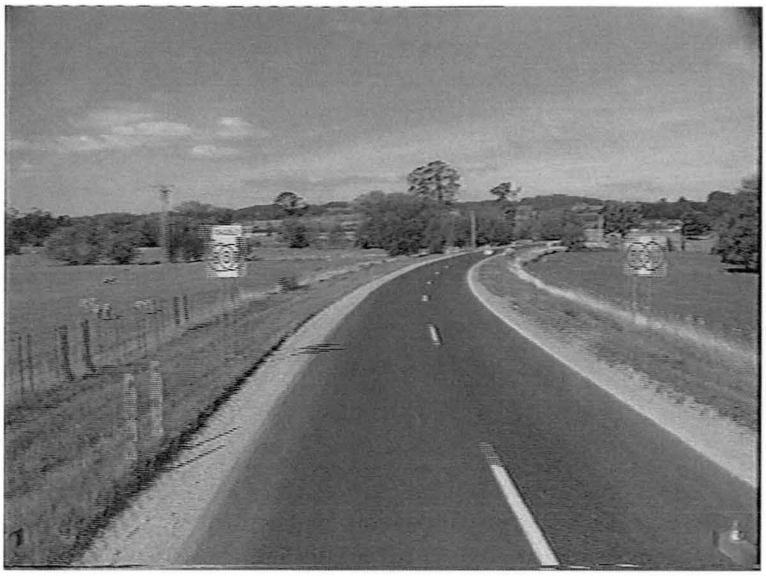


Figure 5.11: An image repetition problem

As shown in Figure 5.12, once the ROI is converted into a binary image using thresholding (the first filtering operation), the resulting objects in the ROI consist of horizontal lines.

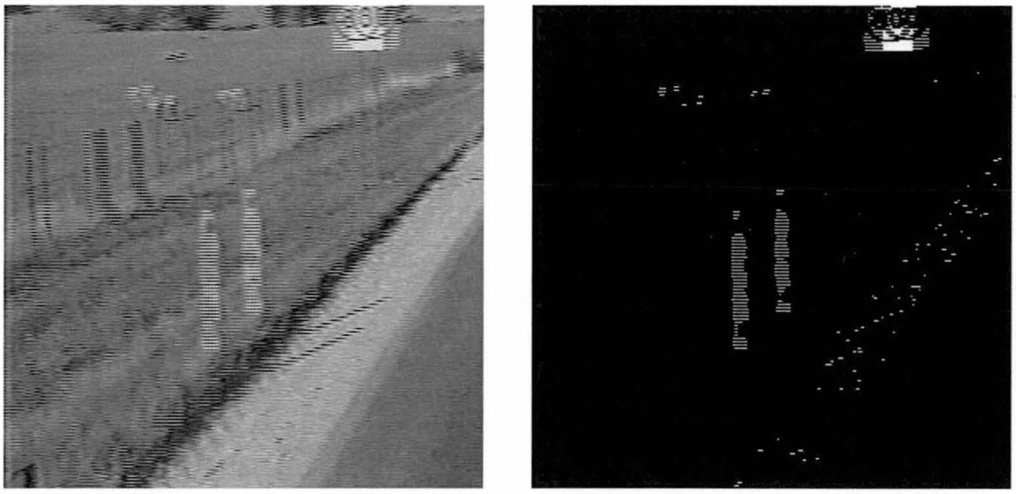


Figure 5.12: ROI for the image of Figure 5.11 (left), and its binary image (right)

The second filtering operation consists of a morphological closing which connects the horizontal lines and produces solid guidepost objects, and a morphological opening using the structural element "disk". The result is the binary image shown in Figure 5.13.

When the final two filtering operations are applied to the remaining objects in Figure 5.13, two sub-images of the same guidepost are produced, as shown in Figure 5.14. The distinctive nature of such sub-image pairs enables a neural network to identify the situation as being the result of a data acquisition error. An alternative criterion for determining if the sub-images are indeed of the same guidepost is the distance between the sub-images. If the distance is less than about 50 pixels (≈0.5 m), this is additional evidence that the sub-images are of the same guidepost, at least under ideal survey conditions, in which guideposts are quite evenly spaced.

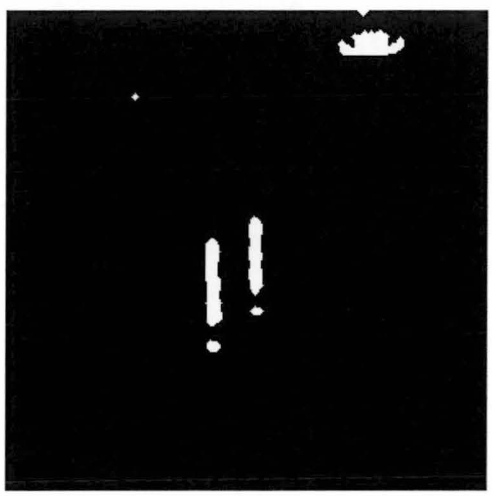


Figure 5.13: Morphological operations applied to duplicate binary images

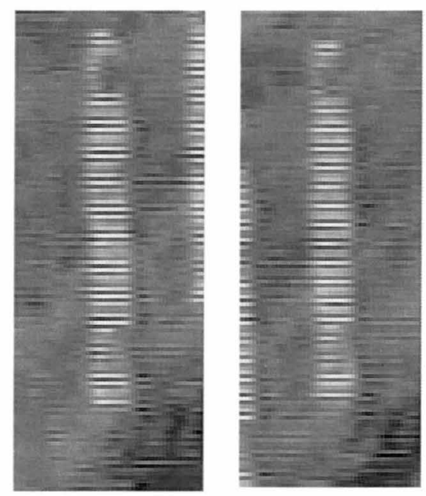


Figure 5.14: Sub-images of the same guidepost

5.3 Performance Evaluation

The basic system described in the previous section was tested under ideal survey conditions, with an image grab rate of one image per second. The tests involved a number of links along the Midland Highway (MH, A0087 Links 5-24) and the Mole Creek Main Road (MC, A1374 Links 6-94) in Tasmania. Table 5.1 summarises the performance of the basic system.

Table 5.1 shows that the basic guidepost survey system performance under ideal conditions is sufficiently good to be confident that the basic system contains all the fundamental aspects necessary for this application. Of the 124 guideposts encountered by the survey, 103 guideposts were captured within an image ROI, correctly identified as candidate FOIs, and then correctly identified as being guideposts. This gives a bulk performance level of 83%, with an associated bulk confidence level of 72%, calculated based on Table 5.2. The problems associated with 17% of the images are analysed in the next section.

Road	Test	Actual posts	Correct count	System Performance	Confidence level
MH	1	22	20	91%	81%
MH	2	11	8	73%	87%
MH	3	19	14	74%	61%
MC	1	11	11	100%	87%
MC	2	24	20	83%	73%
MC	3	21	17	81%	71%
MC	4	16	13	81%	46%
Overall		**124**	**103**	**83%**	**72%**

Table 5.1: Basic system performance under ideal conditions along the Midland Highway (MH) and the Mole Creek Main Road (MC)

Guidepost recognition		**Confidence level**
Yes (No)	***No (Yes)***	
1	0	100%
0.9	0.1	80%
0.8	0.2	60%
0.7	0.3	40%
0.6	0.4	20%
0.5	0.5	0%

Table 5.2: Confidence level of guidepost recognition

5.4 System Extensions

5.4.1 System Performance Under Non-Ideal Survey Conditions

A basic survey system is not expected to be fully reliable under more complex, changing survey conditions. Table 5.3 shows the performance of the system when it was tested under such conditions.

Road	Test	Actual posts	Correct count	System Performance	Confidence level
MH	1	13	9	69%	51%
MH	2	22	15	68%	73%
MH	3	14	9	64%	55%
MH	4	36	20	56%	64%
MH	5	23	10	43%	75%
MC	1	19	6	32%	68%
MC	2	20	13	65%	63%
MC	3	19	5	26%	51%
MC	4	17	9	53%	67%
MC	5	13	9	69%	66%
Overall		**196**	**105**	**54%**	**63%**

Table 5.3: Basic system performance under non-ideal conditions on the Midland Highway (MH) and the Mole Creek Main Road (MC)

Table 5.3 shows that the performance of the basic system under non-ideal survey conditions varied from 26% to 69%. By examining the basic system's performance under non-ideal survey conditions, the additional design requirements of an extended system can be established. Table 5.4 summarises the problem areas.

	Survey condition	
	Non-ideal (196 posts)	**Nearly ideal (124 posts)**
Missed or repeated guideposts		
• Posts not included in the ROI of an image, and not present in the next image	23	9
• Posts appearing in the ROIs of two consecutive image grabs	3	12
Candidate FOIs		
• Posts included in image ROIs, but not identified by the image processing procedures as candidate FOIs within the ROIs	59	9
FOI identification		
• FOIs mis-identified by the FOI identification neural network	41	18

Table 5.4: Problems to be addressed by an extended guidepost survey system

Figure 5.15 provides an overview of the basic system's performance, highlighting problem areas. The square bracket values refer to the basic system's performance under nearly ideal conditions, as examined in the previous section (Table 5.1). The unbracketed values are of its performance under non-ideal conditions.

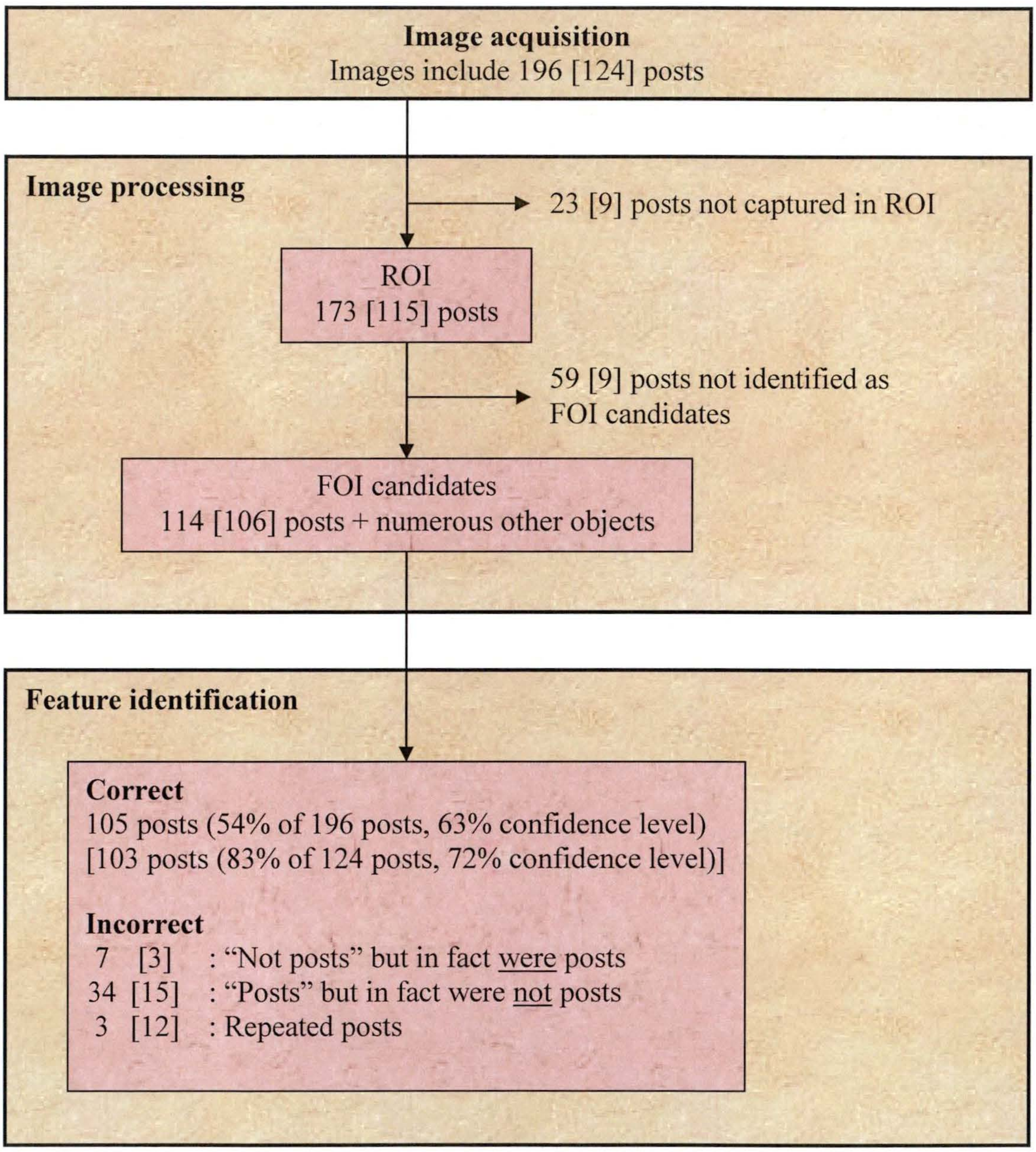


Figure 5.15: Basic system performance overview under non-ideal and ideal [in square brackets] survey conditions

5.4.2 Missed or Repeated Guideposts

Some guideposts were not included in the ROI of an image, and also not present in the next image: an example of this is shown in Figure 5.16. Conversely, some guideposts appeared in the ROIs of two consecutively grabbed images: an example of this is shown in Figure 5.17. The principal causes of these problems are variations in the speed of the survey vehicle, and relatively small or large guidepost separation distances compared to the usual straight road separation distance.

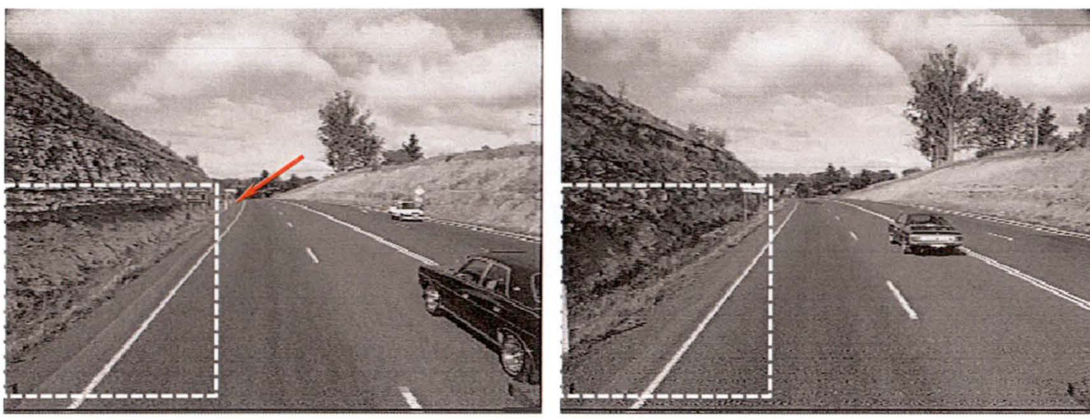


Figure 5.16: Guidepost lies outside the ROI (left), and was passed in the next consecutive image (right)

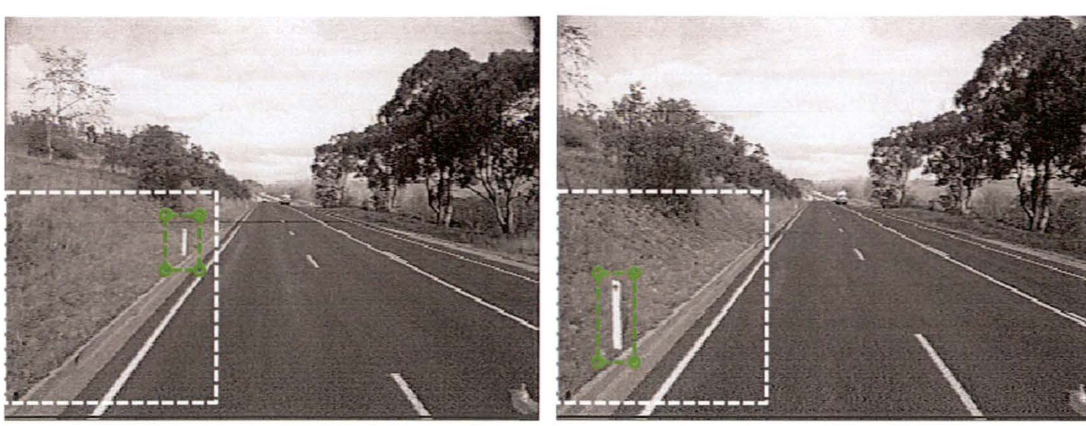


Figure 5.17: The same guidepost appears in the ROI of two consecutive images

One approach to addressing these problems, at least in part, is to develop a supervisory module with the aim of controlling the image grab based on monitoring the vehicle speed, which can be captured as ancillary information by Matlab, and monitoring the FOI content of each ROI. In Figure 5.16, the lack of a guidepost

(FOI) in the ROI should trigger an immediate grab of the next image, while in Figure 5.17, the location of the FOI within the ROI should trigger a slight delay in grabbing the next image. Unfortunately, the archived case study survey footage provided by the State Government of Tasmania for this thesis does not include vehicle speed information.

In addition to adjustment of the image grab rate by a supervisory system, a neural network can be trained to identify guideposts which are captured in successive ROIs. This can be done by designing the neural network to accept two guidepost FOI images as simultaneous input. Such an approach was successfully used by Carter et al. (2000) to identify vehicles captured in successive ROIs, but the caveat in the case of a guidepost survey system is that all guideposts are very similar, and significant background information would need to be included in the FOI image for this exercise to be successful.

5.4.3 Candidate FOIs

The problem of failing to identify a candidate FOI within an ROI means that a guidepost included in an image ROI is not identified as a candidate FOI. Examination of the problem suggests that it is primarily due to departures from the ideal survey condition of strong, diffuse sunlight, and occasionally due to the presence of complex roadside environments.

Changing light conditions

The image processing method for the basic system relies on a significant intensity contrast existing between the white pixels of a guidepost, and the generally darker pixels of the surrounding background. As explained in Section 5.2.2, this intensity contrast enables road images to be converted into binary images, with thresholding used to isolate candidate guidepost FOIs from their surroundings. This works well under the ideal survey conditions of strong, diffuse sunlight.

The image processing strategy of using a threshold of 0.75 for the first filtering operation (see Section 5.2.2) must be changed if the ambient diffuse light level is weak, as shown in Figure 5.18 (left); or if the sunlight is direct and is such that the guidepost surface facing the camera is in shadow, as shown in Figure 5.18 (right). Under such conditions, the guidepost will have a similar intensity, or be darker than, its surroundings, resulting in a poor appearance to motorists as well as the guidepost survey system.

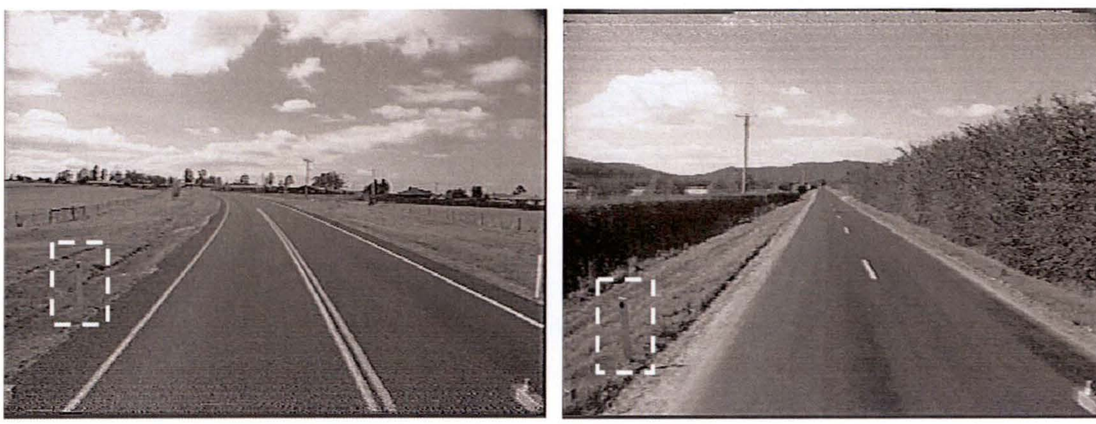


Figure 5.18: Insufficient sunlight (left) and direct sunlight on the rear side of a guidepost (right)

Figure 5.19 shows the strategies appropriate for dealing with decreasing intensity contrast between a guidepost and its surroundings.

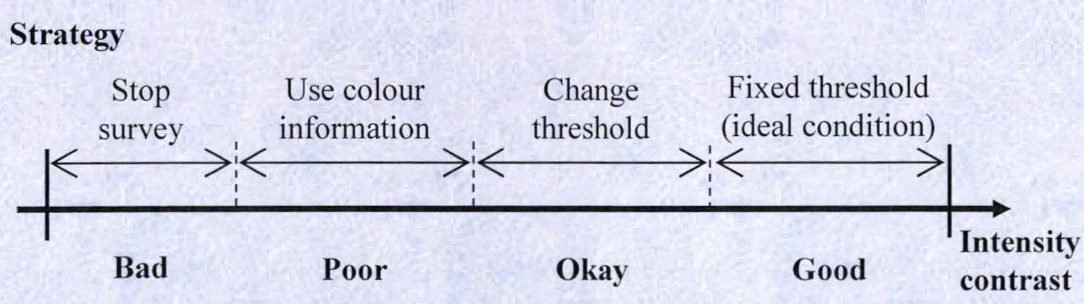


Figure 5.19: System strategies for differing contrast conditions

In the case of a mild reduction in the strength of the ambient diffuse light, simply lowering the threshold value enables guideposts to be identified as candidate FOIs: there is still a significant intensity contrast between the guidepost pixels and the surrounding pixels, but the overall intensity has reduced and the threshold intensity must thus also be reduced. This can be achieved in an extended system that includes a supervisory module to monitor the intensity range of pixels within the ROI, using either an ROI intensity histogram or a neural network, and adjusts the intensity threshold as appropriate.

Figure 5.19 shows that, once the ambient light level falls beyond a certain point, the intensity contrast between a guidepost and its surroundings is reduced to the point that greyscale thresholding does not work. The rule-of-thumb is that, provided the guidepost can still be discerned by the human eye, then it may still be possible to isolate the guidepost sub-image within the ROI. In this case, the image processing strategy should use colour information as an ancillary neural network input, since a guidepost which is unclear in a greyscale image will be more easily identified in a colour image. The options are either to use a neural network which accepts colour intensity image information, or continue to use greyscale image information, but supplement it with colour histogram information, as described in Section 4.3.5.

Complex roadside environment

A complex survey background can also result in failure to identify candidate FOIs within an ROI, as image thresholding can produce a messy binary image if the roadside environment is complex, perhaps because of vegetation. This problem can be isolated by using a neural network to classify the roadside environment as either *Complex* or *Simple*, based on the result of applying image thresholding to the image. If the roadside environment is judged to be *Complex*, additional image filtering efforts will be required to identify candidate guidepost FOIs.

5.4.4 FOI Identification

The problem of failing to correctly determine whether or not a candidate FOI is indeed a guidepost is due to departures from the ideal survey condition of strong, diffuse sunlight; and/or due to the survey system encountering different guidepost designs, such as the use of plastic posts instead of wooden posts, or the use of square reflectors instead of round disk reflectors.

Changing light conditions

The problem of assessing candidate FOIs under light conditions that differ from the ideal conditions of strong, diffuse sunlight can be addressed in an extended system by the same supervisory module developed to address the problem of finding the candidate FOIs within an ROI, as discussed above. The supervisory module is responsible for selecting one of several FOI identification neural networks, each appropriate for a different light condition (i.e. intensity contrast).

Guidepost design

Different guidepost designs are often encountered along different sections of a rural highway, since replacement guideposts installed over periods of many years have slightly different designs. A basic system neural network trained to identify a specific type of guidepost will naturally not work as well if asked to assess an unfamiliar guidepost design.

One option to address this problem is to run the survey system in test mode, gather additional FOI training images, and retrain the FOI identification neural network. Another option is to again provide the neural network with ancillary information about the FOI's colour distribution, since all standard guideposts contain a red reflector.

5.5 Condition Assessment

Physical condition assessment is another significant part of guidepost survey work, and it can also be part of a basic system. A guidepost physical condition assessment system can be developed based on guidelines such as those set out in Table 5.5. Another useful guideline is ROCOND (1990), which assesses guideposts for their ability to provide adequate delineation under conditions of reduced visibility. It ranks the condition of guideposts under five categories, from 1 (excellent condition) to 5 (inadequate condition), based on the delineation of road alignment by guideposts at typical vehicle speeds.

Routine maintenance	Maximum defective condition	Minimum condition after reinstatement
Guidepost cleaning	• Guideposts generally untidy throughout a link through buildup of mildew, moss or grime that is noticeable from a distance of 10 m. • One particularly unsightly guidepost. • On unsealed roads posts to be cleaned annually in spring.	All guideposts within the link to be cleaned and the overall appearance returned to an acceptable level. Unsightly guide post to be cleaned.
Guidepost replacement	• One post missing adjacent to a culvert. • Two consecutive posts are missing. • 10% of posts missing - over a 1 km length. • 5% of posts missing on curves with an advisory speed sign.	Replace all missing posts.
Guidepost resetting	Post varies from standard height by 100 mm or is displaced by 15° from vertical.	Reset and straighten the post.
Guidepost painting	10% of the painted post surface area is peeling or is not suitable for cleaning.	Repaint or replace all posts.
Delineators	Any missing or damaged delineators.	Replace the delineator.
Delineator replacement	Ineffective reflectivity by night time inspection or CIL less than 50% of AS1906.2 new reflective properties.	Clean or replace the delineator to re-establish an effective condition.

Table 5.5: Typical guidepost condition assessment and corrective action guidelines (DIER, 2004)

The manual condition assessment of guideposts requires an inspector to examine each guidepost along the road based on criteria such as those listed in Table 5.5. This is a lengthy and labour intensive process, which can be improved and complemented by automated condition assessment systems. However, good image quality is required for the system to achieve reasonable performance, better image quality than the archived footage used for this case study.

5.6 Basic System Software

5.6.1 System Test Mode

Figure 5.20 provides an overview of the basic guidepost survey system software developed by the author while in test mode. Italicised names refer to Matlab m-files. The system is initialised by *ProStart*, and the principal software routines are *ProGrab* (image acquisition), *ProROIGuideP* (image processing), and *ProGuidePAnalysis* (feature identification), described below.

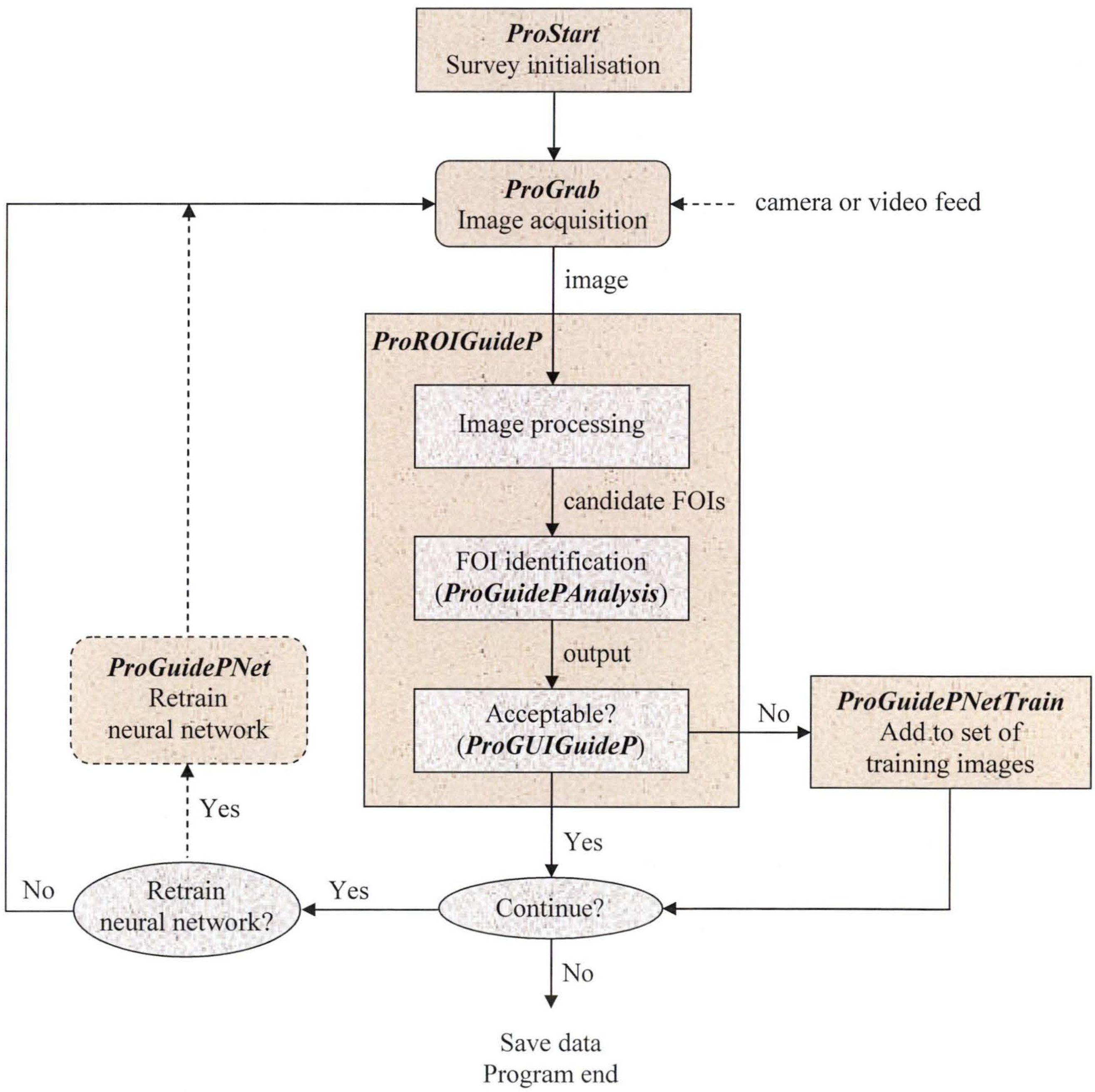


Figure 5.20: Basic survey system test mode software overview

ProStart establishes ActiveX control of the video card driver in preparation for grabbing images from the camera or from archived video feed. It also contains a "Grab" menu button to allow the user to initiate image grabbing at a specific time/location.

ProGrab is called by *ProStart* once the "Grab" button is pushed. It grabs images and stores them for analysis. The images are directed to *ProROIGuideP*.

ProROIGuideP defines the ROI for guideposts, and identifies candidate FOIs within the ROI using image filtering methods: thresholding; morphological closing to connect guidepost pixels; morphological opening to remove small objects; tracing object boundaries; and examining the size and aspect ratio of each candidate FOI. Candidate FOIs are then resized into a standard form, and directed to *ProGuidePAnalysis* as feature identification neural network input.

ProGuidePAnalysis is called by *ProROIGuideP*. It uses a neural network to identify whether or not the input candidate FOI is a guidepost. It also provides the level of confidence of each analysis result.

In survey system test mode, the result of the analysis of each candidate FOI by *ProGuidePAnalysis* is presented to the user (by *ProGUIGuideP*), who is prompted to confirm the analysis result. If the analysis result is either incorrect, or correct but with a low level of confidence, the candidate FOI image will be added to the neural network training set by *ProGuidePNetTrain*. The neural network is then retrained by *ProGuidePNet* from time to time in light of the new additions to its training data.

The entire image grabbing and analysis process takes less than 1 second for each image. After each analysis, *ProStart* asks if the user wants to analyse the next image, retrain the neural network, or quit the program.

5.6.2 System Operating Mode

Figure 5.21 provides an overview of the software developed for the basic guidepost counting system in operating mode. The programming routines for the survey system operating mode are slightly different to those of the system test mode. They include an addition GUI routine, *ProGUIInput*, which prompts the user to specify the total survey duration and image grab rate. In addition, *ProStart* examines the total number of guideposts identified, and the overall level of confidence for guidepost identification.

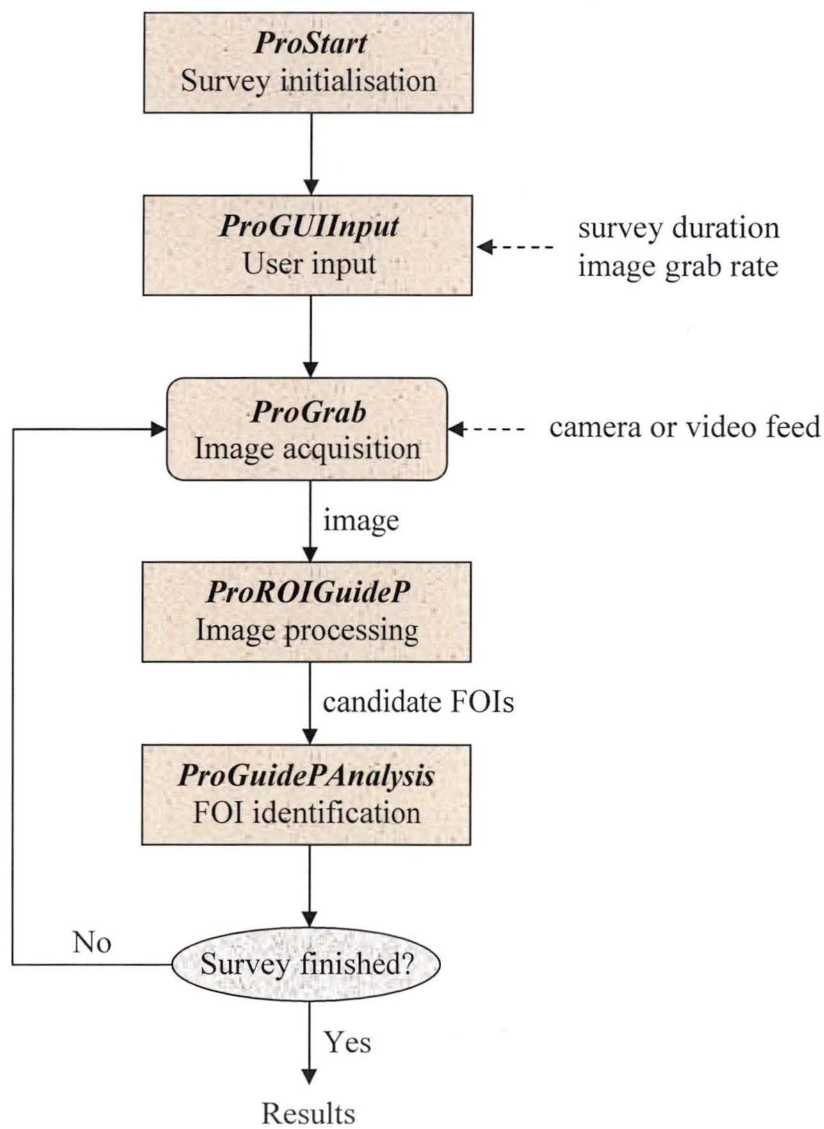


Figure 5.21: Basic survey system operating software overview

5.7 Summary

This chapter has presented a guidepost counting case study to illustrate the generic survey system design approach presented in Chapter 4. Based on this generic design and its associated design application principles, a basic automated guidepost survey system was developed, and confirmed to perform well (83%) under ideal survey conditions: fair weather conditions with good diffuse sunlight, constant survey speed, straight road sections, and a simple roadside environment. This shows that the basic survey system correctly incorporates the fundamental needs of an automated guidepost survey system.

Although 83% is a reasonable performance achievement, there is a clear need for the survey system to achieve a higher level of performance over longer survey distances, with associated challenges in terms of changing survey conditions. A road authority would typically require a road maintenance contractor to carry out surveys at about the 90% performance level.

To this end, the basic system's performance under more complex survey conditions was examined, and the needs of an extended survey system able to perform well under such conditions were identified. An extended guidepost survey system which incorporates the principal corrections is presented in Chapter 7.

6.0 A BASIC CENTRELINE CONDITION SURVEY SYSTEM

6.1 Introduction

The basic guidepost counting system developed in Chapter 5 is an example of an automated survey system whose main goal is simply feature identification. This chapter presents a case study of double centreline-marking condition assessment. The basic survey system presented in this chapter is again based on the generic design approach described in Chapter 4. As usual, the survey system's three major components are image acquisition; image processing; and feature identification & condition assessment. The fourth survey system component, follow-on analysis by an expert system, is also demonstrated.

Unlike feature identification, a neural network developed for condition analysis requires clear images of road features so that their condition can be analysed in detail, since analysing indistinct images cannot give reliable results. Hence, more effort needs to be applied to image processing to ensure better image quality compared to that needed for the guidepost survey system.

This case study examines the white longitudinal centrelines used to separate opposing directions of traffic flow on pavements with a width greater than 5.5 m. On roads narrower than this, centrelines are not usually provided other than where sight distances for overtaking are deficient. Centrelines may be continuous or broken single lines (separation lines); or continuous double or single lines with parallel broken lines (barrier lines). This case study examines only double lines. Barrier lines are not used on pavements of insufficient width where it is not practicable for all vehicles to travel on their side of the line.

Raised pavement markers are used in conjunction with, or sometimes used instead of, painted line-markings. The two marker types are Non-Retro-reflective Pavement Markers (NRPMs) and Raised Retro-reflective Pavement Markers (RRPMs or "cat's eyes"). NRPMs are used at intersections to provide guidance to drivers. RRPMs are used to augment painted lines or, in conjunction with NRPMs, to simulate painted lines. They are also used instead of painted lines for the provision of lane lines, separation and barrier lines, edge lines, and traffic islands and medians. They are not obscured at night under wet conditions, as the retro-reflective panels (see third dot point below) sit above the surface and are more prominent than reflectorised painted markings. In addition, they provide an audible and tactile signal when traversed by vehicle wheels.

In Tasmania, RRPMs are used to highlight centreline-marking on all rural roads that have a sealed width greater than 6.4 m. They are also applied to the centrelines and outside the edge lines on all national highways in Australia, and on dual carriageways with no street lighting. They are used in various colours for different purposes.

6.2 Condition Assessment Criteria

Line-marking is intended to provide clear guidance to motorists both during the day and at night. It must be maintained in good condition to ensure its effectiveness and appearance. Typical maintenance of line-marking requires the replacement of worn or missing marking components.

The condition of line-marking can be rigorously assessed by measuring its reflection. There are three basic types of reflection (Brown & Bliss, 2004; Main Roads, 2000):

- diffuse reflection results when light strikes a microscopically rough surface, reflecting a small amount of light along the path of the incoming light beam;
- mirror reflection results when light strikes a surface which is microscopically smooth and is reflected from the surface at an equal but opposite angle to that of the incident light beam; and
- retro-reflection results from the addition of glass beads to the wet paint film during line-marking, reflecting the light from a vehicle's headlamps back towards the driver, irrespective of the angle of the incident light beam.

Line-marking is normally painted with the addition of retro-reflectivity materials (glass beads), since diffuse reflection materials alone have low night time visibility, while mirror reflection materials reflect light directly to the source only when the light beam is perpendicular to the surface. Therefore, the condition of line-marking is usually assessed by measuring its retro-reflectivity.

Retro-reflectivity is measured by the coefficient of luminous intensity (CIL), defined as the ratio of the luminance of a surface (millicandela / m^2) to the illumination (lux) falling on the surface. The CIL thus has units of mcd/lux/m^2. For example, the minimum requirement of retro-reflectivity for line-marking in Tasmania is a CIL between 150 to 200 mcd/lux/m^2. Figure 6.1 shows the Laserlux 6 Mobile Retro-reflectometer developed by MLT (2005), which uses laser beam reflection to determine the pavement marking retro-reflectivity. Another typical type of retro-reflectometer is the Mirolux series, as shown in Figure 6.2 (Carnaby, 2001; Mirolux, 2006; TAPCO, 2005).

Figure 6.1: Laserlux Mobile Retro-reflectometer developed by MLT (2005)

Figure 6.2: A Mirolux 30 retro-reflectometer (TAPCO, 2005)

If a retro-reflectometer information is not available, the condition of line-marking is assessed by visual inspection. This typically involves an inspector comparing the total length of a road segment against the condition description which best describes the line-marking's average condition over the segment length. The ROCOND (1990) manual, which is widely used in Australia, assesses line-marking condition by assigning a score between 1 (excellent) and 5 (inadequate), based on the condition of the line-marking, including its delineation in daylight.

6.3 System Design

6.3.1 System Startup and Image Acquisition

This component is virtually identical to that used by the guidepost counting system in the previous case study. It includes a GUI to initialise the system, and prompts the user to specify an image grab rate. For line-marking surveys, an image grab rate of 2 images per second is appropriate, corresponding to about 10 m between images at a survey speed of 80 km/h.

6.3.2 Image Processing

Region of interest

The camera orientation for the centreline-marking survey system provides the same forward-looking wide view as the guidepost survey system presented in Chapter 5, since the same archived survey footage is used for both case studies. Once a road image is grabbed, the Region of Interest (ROI) of the image is identified to be a 100 × 300 pixel region covering a range of coordinates (401:700, 451:550) for an image with 576 × 768 pixels, as shown in Figure 6.3.

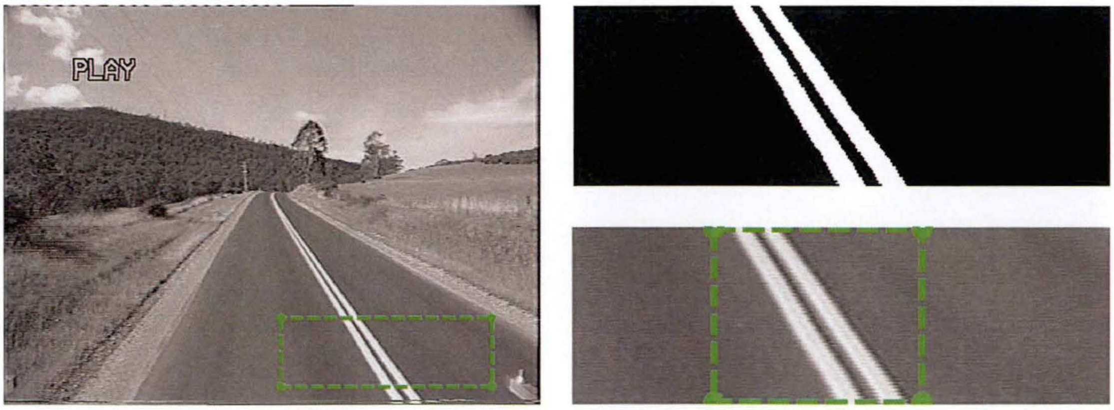


Figure 6.3: Region of interest for centreline-marking

Isolation of candidate feature of interest

As shown in Figure 6.3, the ROI is converted into a binary image by an intensity filter, using a threshold of 0.7 (≈179 greyscale intensity) to isolate the centreline-marking, which is the Feature of Interest (FOI), from the background pavement. The binary image contains values of 1's for the line-marking pixels, and 0's for the pavement pixels.

A dilation operation is then applied to ensure that all pixels corresponding to the FOI are recognised as such. This is particularly important when dealing with an image of line-marking which is either in poor condition, or is unclear due to low ambient light levels.

The bottom right image in Figure 6.4 shows a dilation applied to the binary image produced from an image of poor condition line-marking. The operation dilates each white pixel in the binary image linearly to 25 pixels on each side of the pixel along a line at a direction of 120° anticlockwise from the positive x-axis. This angle is only an approximation of the slope of line-marking, as the exact slope of the line-marking is not required for this operation under ideal survey conditions. As shown in Figure 6.4, the poor condition line-marking has been successfully identified in binary form, which allows the ROI to be further cropped to removed unwanted portions.

Figure 6.4: Identification of poor condition centreline-marking, with the binary threshold filter supported by a dilation using structural element "line"

The dilation performances of structural element "line" distances of 30, 50 and 70 pixels were examined with a number of images. A distance of 50 pixels was found to be appropriate, as used in the example of Figure 6.4. A shorter distance was not always sufficient to connect the poor line-marking pixels, while a longer distance occasionally resulted in pavement pixels outside of the line-marking area being interpreted as line-marking pixels.

The section of the ROI that contains the FOI is windowed out by identifying the coordinates of the far left and right white pixels in the binary image. This allows the ROI to be further cropped to remove more than half of the unwanted pavement portions. Unlike a guidepost survey, each ROI of the centreline-marking only contains one candidate FOI, which may or may not be the continuous double lines which are the target of this survey.

6.3.3 Feature Identification and Condition Assessment

In the previous case study, a neural network was used to determine whether or not a candidate FOI contained a guidepost. In this survey system, image processing methods alone are adequate for this task, at first pass. Examining the total width of the line-marking within a candidate FOI is sufficient to identify it as either a) double line; b) a single line; or c) another line-marking type. A standard double line has a width between 20 to 40 image pixels for the camera orientation, image resolution and ROI of this survey. Total line widths less than 20 pixels are identified as single lines, and line widths greater than 40 pixels are identified as other line types, examples of which are shown in Figure 6.5.

This approach to determining whether or not a candidate FOI indeed contains a continuous double line has a problem, namely that a single continuous line with an adjacent broken line will be mis-identified as a continuous double line. For the purpose of this case study, this is not treated as a mis-identification, and is accepted as a correctly identified FOI. In a refined survey system, the problem can be overcome by training a neural network to examine a "preliminary" ROI large enough to enable recognition of the difference between the two line-marking types.

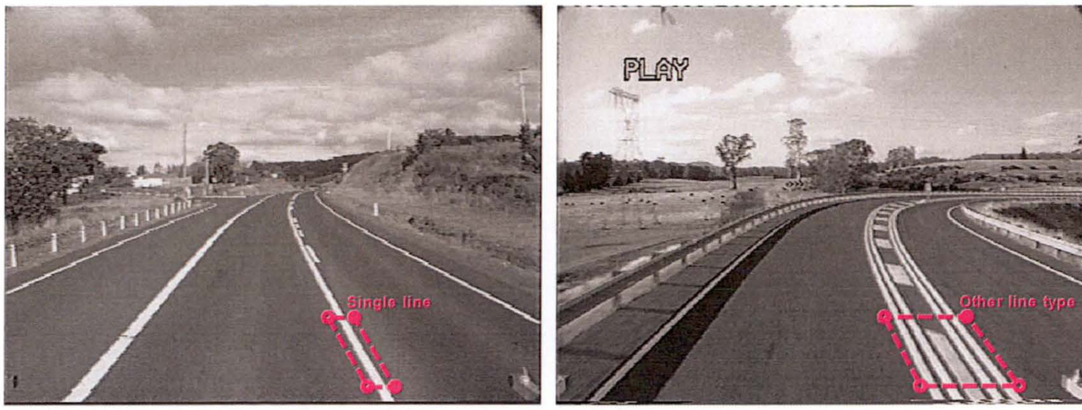


Figure 6.5: Line types identified as "other" than continuous double lines

Image manipulation to standard form

Figure 6.6 shows the double line-marking windowed out from Figure 6.3. The geometry of the line-marking is inclined, and rotating it into a top-down form is useful for later analysis. The slope of the line-marking can be approximately determined using the coordinates of any two pixels on either boundary of the white lines, as shown in Figure 6.6. A Matlab program was written to calculate the slope and hence the rotation angle (90°-θ).

Figure 6.7 (left) shows the double line-marking after rotation by the Matlab *imrotate* function. A sub-image that contains only the line-marking and its immediate neighbourhood is then established, as shown in Figure 6.7 (right), by first identifying a rectangular matrix at the centre of the rotated line-marking image, with an allowance of 10 pixels from each side of the line-marking boundary. The top and the bottom of this rectangular matrix are then extended laterally until they touch the first black pixels (pixel values equal to 0's) at the top and the bottom respectively.

Figure 6.6: The centreline-marking FOI

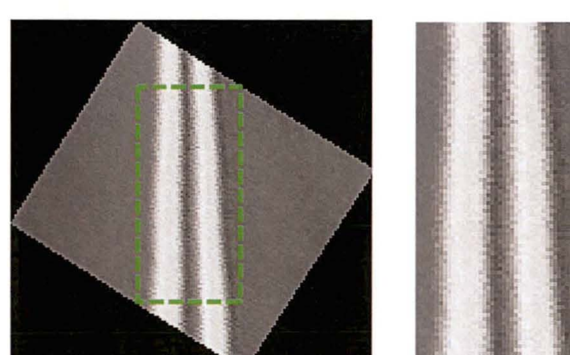


Figure 6.7: Rotated FOI (left) and sub-image of centreline-marking (right)

Condition assessment

A 3-layer feed-forward neural network was established to assess the condition of the line-marking. The neural network contains 100 neurons with log-sigmoid transfer functions in both the input layer and the hidden layer, and two neurons with pure-linear functions in the output layer. As a neural network can only accept a fixed number of input values (greyscale pixel intensities), each line-marking FOI sub-image is resized into a standard 90 × 30 pixel image, and the neural network is designed to accept (90 × 30 =) 2700 input values.

In addition, as discussed in Section 4.4.3, the pixel values are rescaled to the effective input range (about 10) of a log-sigmoid transfer function. The rescaling operation speeds up the task of training the neural network, and need only be approximately correct, because the training algorithm will fine-tune the weights and biases associated with each neuron to make best use of the transfer function.

The two output neurons correspond to *Good* and *Poor* line-marking condition. This is not as rigorous as the five point ROCOND (1990) system often used in manual surveys, but in consultation with Mr. Jan Lang (Tasmanian Government, Manager of Asset Information) it was agreed to be a necessary consequence of using archived survey footage taken with a wide-view forward looking camera. A five-point condition assessment version of the survey system could be implemented based on images taken by a more downward looking camera with good resolution.

The neural network has a similar architecture to the one developed for guidepost identification, presented in Chapter 5, and the software routines that carry out the neural network training and implement its use within the survey system are also similar, thereby applying the design principle of software modularity. The neural network was trained under the ideal survey conditions associated with basic survey systems, using 40 sample images obtained along the Midland Highway in Tasmania. Here, ideal conditions are straight road sections, sufficient light that the line-marking has good reflection, dry weather, and a constant survey speed.

The line-marking condition in each of the training images was manually assessed to be either *Good* or *Poor*, and the neural network was trained by assigning output values of [*Good*, *Poor*] = [1, 0] or [0, 1] as appropriate. When the neural network is presented with an FOI image other than a training image, the two pure-linear transfer function outputs are constrained to the approximate range of 0 to 1, with the actual value denoting the degree of certainty in the neural network's assessment.

Figure 6.8 shows typical outputs from the neural network. Additional training images were added during the survey system test mode, to extend the ability of the neural network to correctly assess the line-marking condition.

Figure 6.8: Centreline condition assessed by a neural network

6.3.4 Follow-on Analysis: Consideration of Context

The consideration of context is an important aspect of road feature surveys, as discussed in Chapter 4, since the relative importance of the assessed condition of a road feature depends on context. Follow-on analysis is the fourth component of a survey system, and its results need to be tailored to the requirements of decision-makers, who must determine budget priorities for highway maintenance work.

This case study uses horizontal road alignment to illustrate how context can be taken into account in a basic survey system. The role of context in this example is straightforward: if the line-marking is in poor condition, then accidents are more likely to happen on a winding road section than on a straight road section, as shown in Figure 6.9. Other forms of context that might be considered include roadside environment (e.g. adjacent slopes versus flat ground), and the posted speed limit.

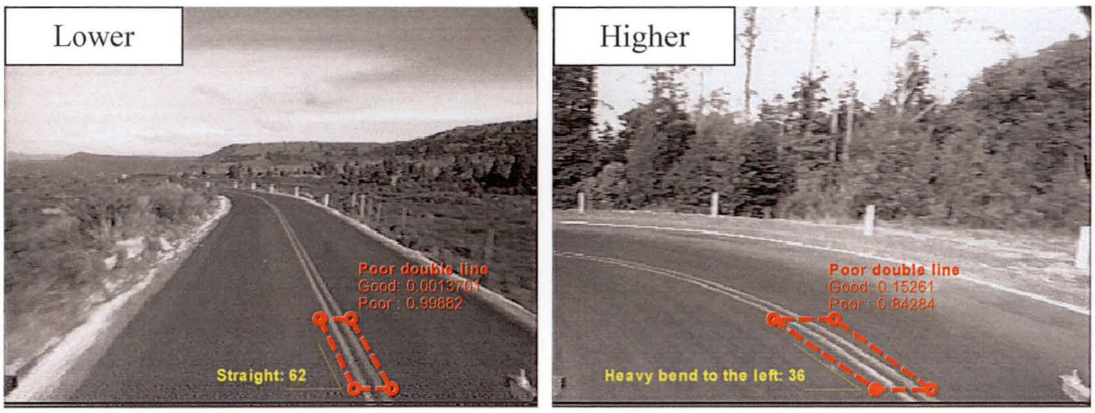


Figure 6.9: Condition assessment with consideration of context

An expert system provides a natural and elegant tool for the consideration of context, and Section 3.4 and Appendix C review expert system theory. The expert system for the present exercise requires two inputs: the line condition assessment score, and some measure of the road's horizontal alignment. This latter can be determined in a variety of ways, one option being to use Global Positioning System (GPS) data to link the position of the image being considered to a highway alignment database prepared from the infrastructure authority's highway design drawings.

Equipping a survey vehicle with GPS and acquisition of database information by the Matlab software package would be straightforward. However, since digital information on highway alignments is not available in Tasmania, an image processing routine was instead developed by the author to identify the horizontal road alignment in terms of the degree of curvature in the centreline-marking. This approach is not sufficiently accurate to be acceptable in practice, but serves to illustrate the use of an expert system.

As shown in Figure 6.10, the centreline on a straight section of highway has an orientation of about 65° with respect to the horizontal axis of an image in the survey footage used for this case study. A centreline orientation less than 65° indicates a bend to the left; and an orientation greater than 65° indicates a bend to the right.

Figure 6.10: Approximate measure of horizontal road alignment

The expert system developed for this exercise has input variables *Geometry* and *Condition*, and an output variable *Overall*. Ten images from a short section of highway are used to demonstrate the expert system's usage, and only bends to the left were present in these images, so the variable *Geometry* ranges from 20° to 65°.

The basic centreline survey system developed for this case study assesses centreline condition as either *Good* or *Poor*: as discussed, this is a consequence of the camera set up used for the survey. A five point assessment scheme, or a continuous scheme, would be enabled by a more survey-specific camera orientation, and hence the variable *Condition* in this demonstration expert system ranges from 0 (bad) to 10 (good). The line-marking condition score on the 0-10 scale was assessed manually for each of the ten demonstration images.

Both input variables are fuzzified using the sigmoid membership functions shown in Figure 6.11. These membership functions are *Bend* and *Straight* for *Geometry*, and *Bad* and *Good* for *Condition*. Note that membership function values (i.e. the degrees of membership) do not need to sum to one. The output variable, *Overall*, represents the modified centreline-marking condition score, with consideration of context, and has the same 0 to 10 range as the input variable *Condition*. It is represented by two sigmoid membership functions, *Bad* and *Good*, and a Gaussian membership function, *Normal*, as shown in Figure 6.12. The centroid method was used to "defuzzify" the expert system output.

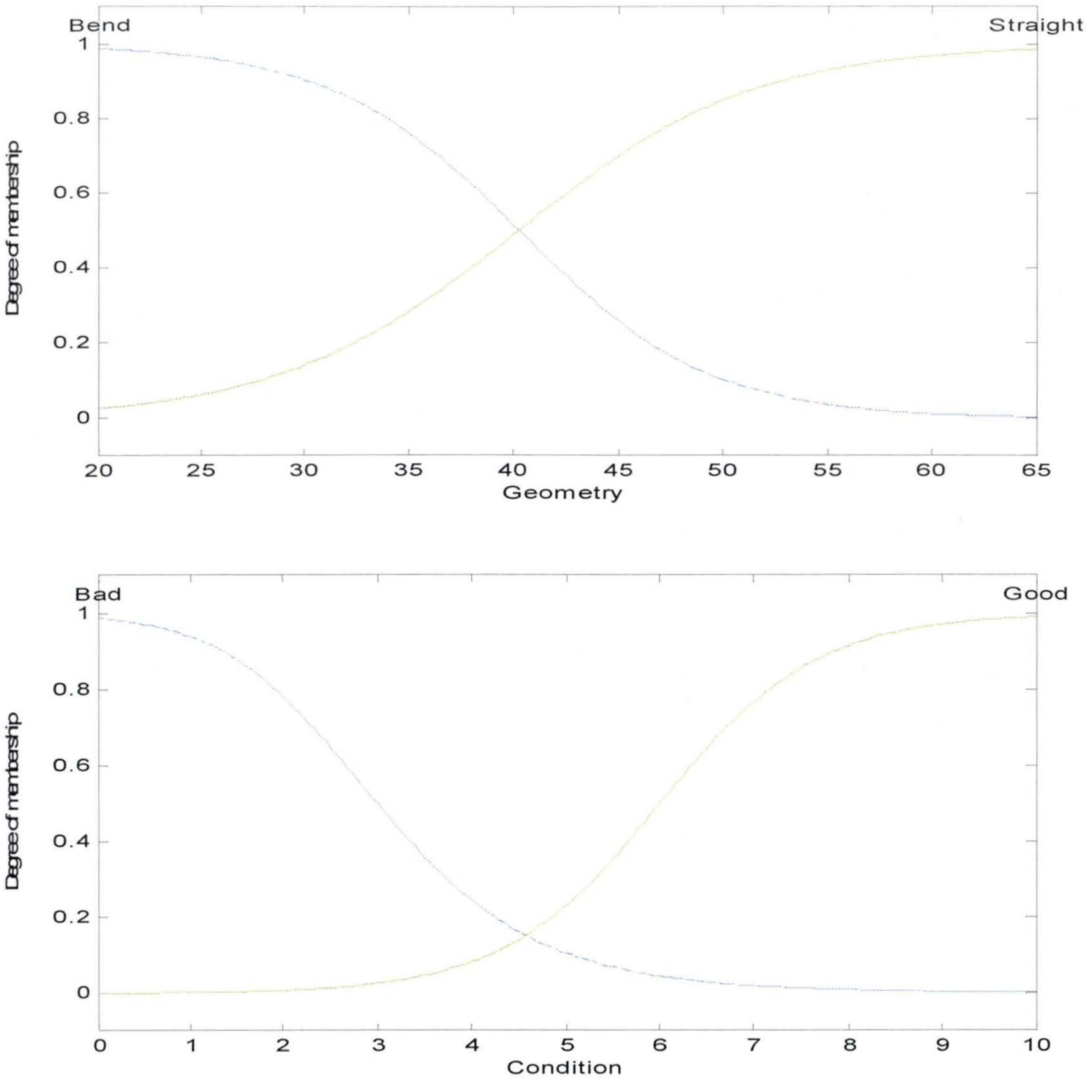


Figure 6.11: Input variable membership functions

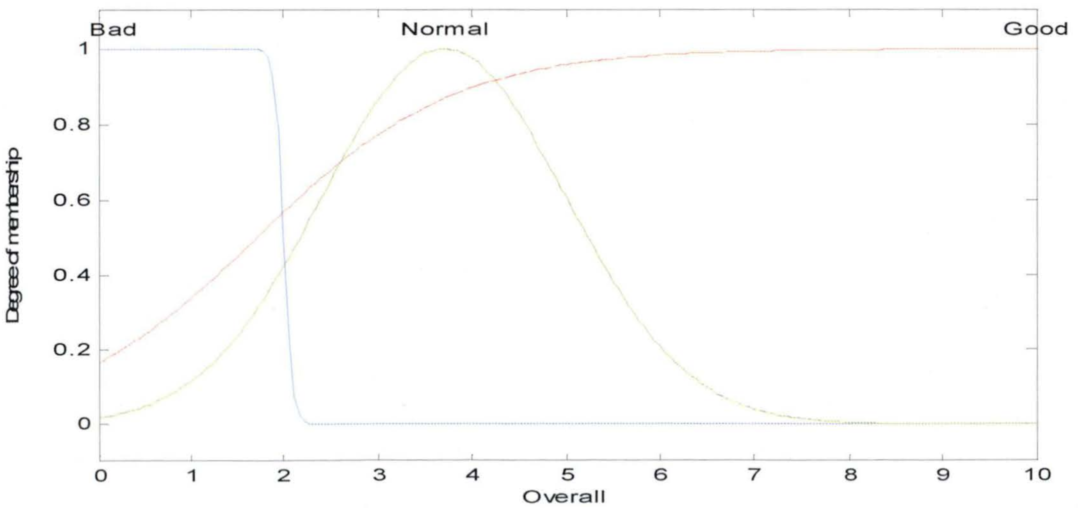


Figure 6.12: Output variable membership functions

The expert system rules, which all carry equal weight, are:

IF (*Geometry* is *Straight*) AND (*Condition* is *Good*) THEN (*Overall* is *Good*)

IF (*Geometry* is *Straight*) AND (*Condition* is *Bad*) THEN (*Overall* is *Normal*)

IF (*Geometry* is *Bend*) AND (*Condition* is *Good*) THEN (*Overall* is *Normal*)

IF (*Geometry* is *Bend*) AND (*Condition* is *Bad*) THEN (*Overall* is *Bad*)

IF (*Condition* is *Good*) THEN (*Overall* is *Good*)

IF (*Condition* is *Bad*) THEN (*Overall* is *Bad*)

IF (*Geometry* is *Straight*) THEN (*Overall* is *Normal*)

IF (*Geometry* is *Bend*) THEN (*Overall* is *Bad*)

Figure 6.13 shows the decision surface generated by the expert system for context-based condition assessment.

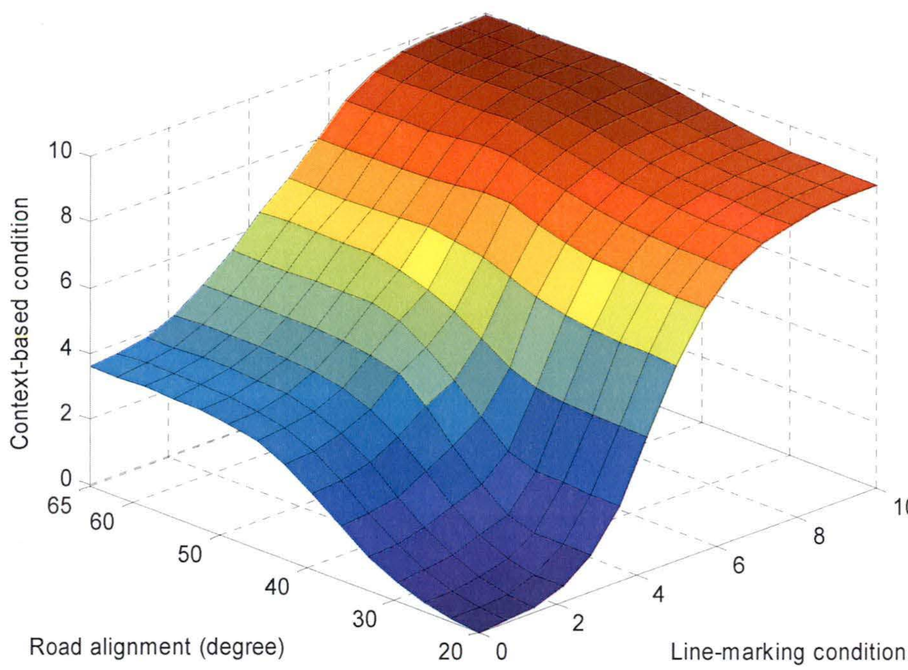


Figure 6.13: Decision surface for context-based centreline condition assessment

An expert system is a totally transparent decision-making tool. The decision surface in Figure 6.13 maps out the output values corresponding to all possible combinations of input variable values, and if the decision surface is deemed to be acceptable then, by definition, the expert system's performance is acceptable.

6.4 Performance Evaluation

The basic line-marking survey system was applied to several Tasmanian roads and highways: the Midland Highway (MH, A0087 Links 5-24), the Lyell Highway (LyellH, A0197 Links 5-20), the Mole Creek Main Road (MC, A1374 Links 6-94), and the Lake Highway (LakeH, A0100 Links 82-93). An image grab rate of two images per second was used.

The basic system's performance when tested under ideal conditions is shown in Table 6.1, calculated as the percentage of images identified correctly in terms of:

a) Line type (double line; single line; or another line type).

b) Line condition (good or bad). The correct condition was determined by the author, with cross-checks by Mr. Jan Lang, the Tasmanian State Government's Manager, Asset Information.

Table 6.1 shows that the overall performance of the basic survey system is about 92% when tested under ideal conditions, confirming that it contains the fundamental aspects of an acceptable line-marking condition survey system. The confidence level of 70% is associated with the correct assessment of the double line-marking condition, not with the correct identification of the double line FOI.

Road	Actual double lines	Correct double lines	Correct condition	System performance	Condition confidence
MH	103	103	102	99%	96%
MH	107	106	101	94%	67%
MH	48	47	43	90%	61%
LyellH	116	113	102	88%	69%
LyellH	77	75	71	92%	70%
LyellH	43	42	34	79%	53%
MC	51	49	48	94%	71%
MC	81	74	70	86%	62%
LakeH	49	49	47	96%	68%
LakeH	89	82	82	92%	86%
Overall	**764**	**740**	**700**	**92%**	**70%**

Table 6.1: Basic system performance under ideal conditions

Consideration of context

A follow-on analysis was made of 10 FOI images to determine their line-marking condition with consideration of horizontal alignment. Table 6.2 summarises the results, and clearly shows that in cases where a poor line-condition occurs in association with a bend, the revised condition assessment is significantly lower than the a priori assessment.

Alignment	Condition	Revised condition	Ranking comparison
59°	9.6	9.9	1 → 1
53°	9.5	9.8	2 → 2
20°	9.0	8.8	3 → 4
65°	8.8	9.4	4 → 3
31°	7.0	6.4	5 → 6
62°	6.5	6.7	6 → 5
48°	5.2	5.5	7 → 8
59°	5.0	5.6	8 → 7
64°	2.5	2.6	9 → 9
26°	2.1	0.8	10 → 10

Table 6.2: Context-based centreline condition assessment

As noted, there is no need to examine Table 6.2 to evaluate the mathematical performance of the expert system, since an acceptable decision surface was mapped out by every combination of inputs. However, experience of artificial intelligence within the transport industry has shown that cross-checking an expert system's results against case study situations in which specific outcomes are expected often leads to minor refinements of the expert system (Dr. Steve Carter, pers. comm.)

6.5 System Extensions

6.5.1 System Performance Under Non-Ideal Survey Conditions

Table 6.3 shows the basic survey system's performance when tested under non-ideal conditions, including changing light levels and road alignments, along the highways listed above, but on different sections; and also on the Gordon River Road (GR, A1727 Links 6-36).

Road	Actual double lines	Identified double lines	Correct condition	System Performance	Condition confidence
MH	66	63	57	86%	64%
MH	88	73	58	66%	56%
LyellH	76	70	64	84%	58%
LyellH	147	132	97	66%	68%
GR	86	49	36	42%	52%
GR	16	15	6	38%	35%
MC	56	49	46	82%	61%
MC	81	62	58	72%	75%
LakeH	65	54	46	71%	92%
LakeH	85	77	65	76%	58%
Overall	**766**	**644**	**533**	**70%**	**62%**

Table 6.3: Basic survey system performance under non-ideal conditions

The overall performance of the basic system when tested under non-ideal conditions dropped from ~92% to ~70%. Table 6.4 summarises the problem areas to be addressed by an extended survey system, as discussed in the next section. These problem areas are also shown in Figure 6.14, which provides an overview of the basic system's performance. The square bracket values refer to the basic system's performance under nearly ideal conditions, as examined in the previous section (Table 6.1).

	Survey conditions	
	Non-ideal (766 FOIs)	**Ideal (764 FOIs)**
Candidate FOIs • Line-marking not identified by the image processing procedures as candidate FOIs within the ROIs	39	5
FOI identification • FOIs mis-identified by image processing	84	20
Condition assessment • FOIs mis-identified by the condition identification neural network	110	39

Table 6.4: Problems to be addressed by an extended survey system

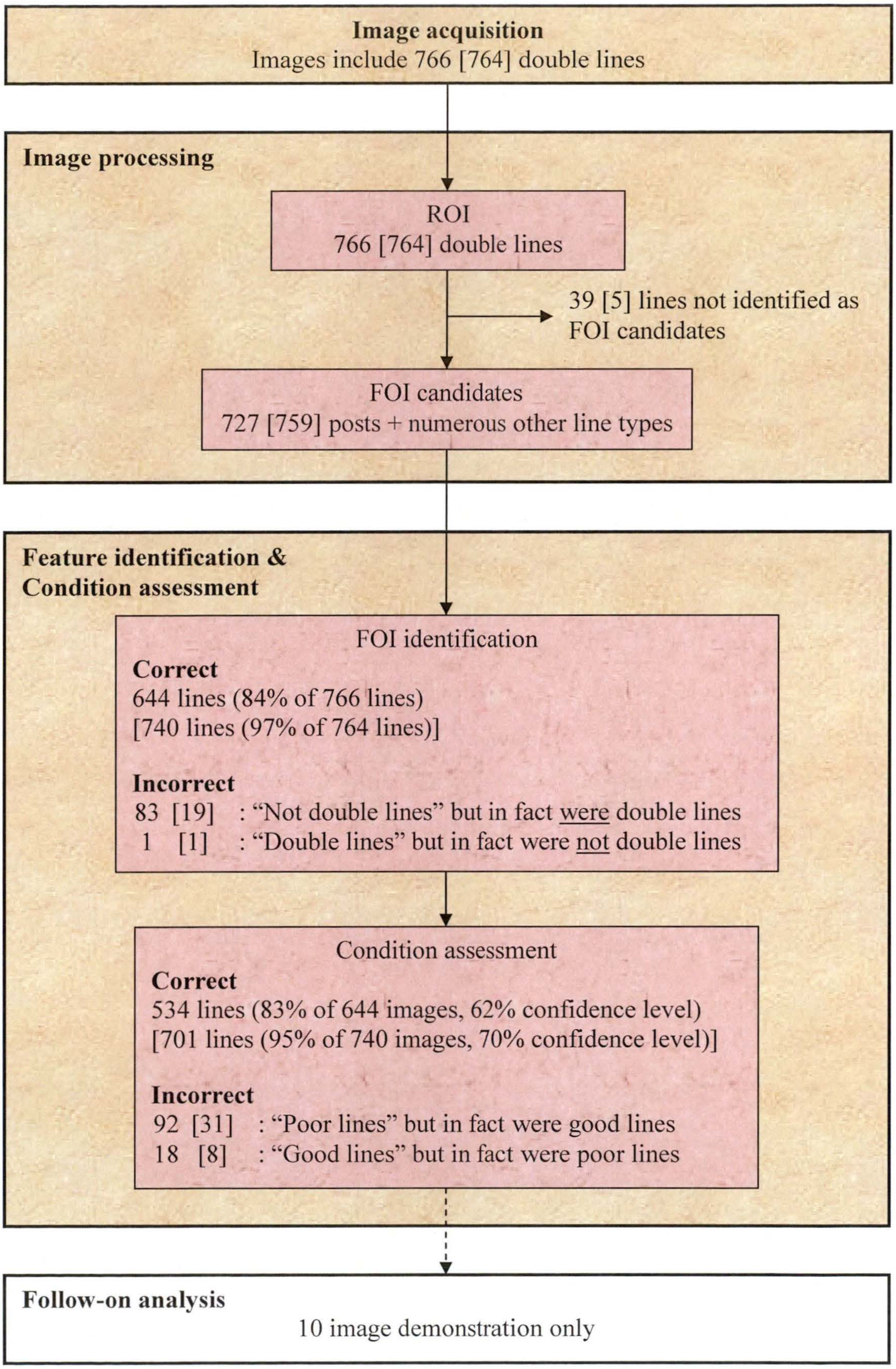


Figure 6.14: Basic system performance overview under non-ideal and ideal [in square brackets] survey conditions

6.5.2 Candidate FOIs

The problem of failing to identify a candidate FOI within an ROI means that double centreline-marking included in an image ROI is not identified as a candidate FOI. Examination of the problem suggests that it is primarily due to departures from the ideal survey condition of strong, diffuse sunlight, and occasionally due to the unexpected road horizontal alignment leading to inappropriate ROI.

Figure 6.15 shows that ambient light conditions during the Lyell Highway survey were occasionally poor, resulting in weak contrast between the white line and the pavement surface that caused an unclear appearance of the line-marking. Changes in the ambient light level was found to be the major problem associated with FOI identification, for similar reasons to those discussed in the guidepost survey system: filtering using a fixed binary threshold for feature isolation (Section 6.3.2) failed to work well when the light level of the surrounding was changing.

Changing road alignment was another problem area that needs to be addressed by an extended survey system. For example, Figure 6.16 shows that the ROI failed to properly capture the centreline at a bend, and thus could not be identified by the system. One option to overcome this problem is to establish a neural network to define the ROI for different road geometry (bends), and another option is to identify the road edges and locate the ROI midway between them.

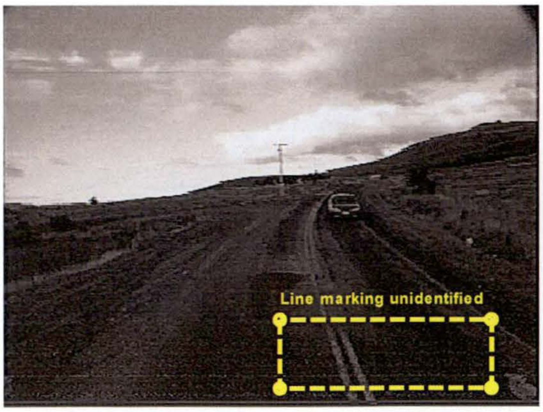


Figure 6.15: Dark environmental conditions at Lyell Highway

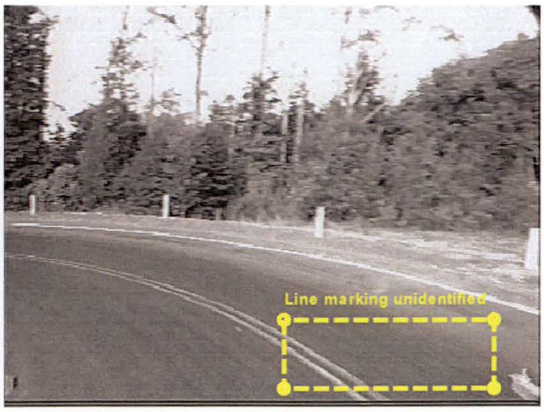


Figure 6.16: Centreline falls outside the pre-defined ROI at a bend

A third problem is that of failure to identify line-marking in very poor condition. The basic survey system is able to detect line-marking in poor to excellent condition, but fails to detect line-marking in very poor condition. Figure 6.17 shows a section of Gordon River Main Road, where the condition of the centreline-marking was so bad that the basic survey system failed to detect any line-marking in the section.

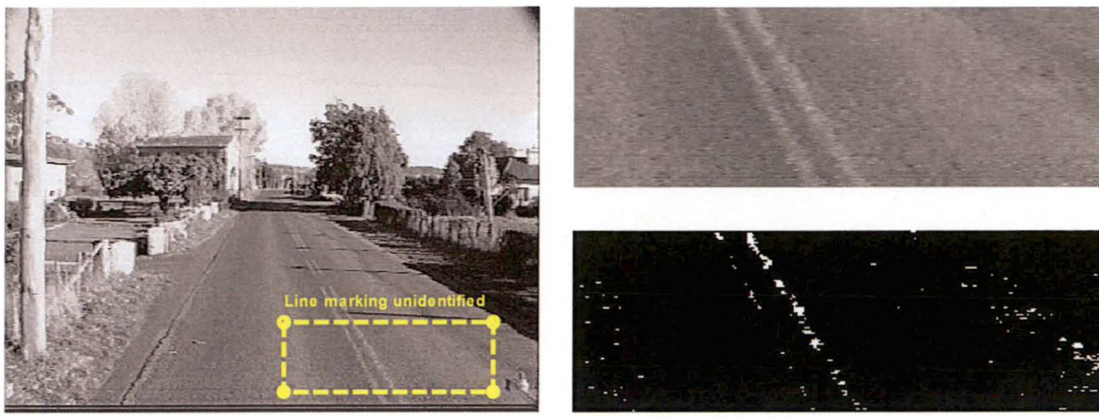


Figure 6.17: Poor centreline could not be identified at Gordon River Main Road

A rule-of-thumb is that if a feature in an image is visible to the human eye, then a suitably trained neural network should also be able to detect the feature. However, such work is certainly the domain of an extended survey system, since additional image processing efforts will likely be required to support the neural network, and the use of a supervisory module may be required.

An alternative solution is to set the line-marking condition rating of a highway section to be poor as the baseline condition, if the section is pre-determined to contain line-marking: such information could be contained in a highway information database and linked to survey images using GPS/GIS technology, which Matlab can easily incorporate. This somewhat pragmatic solution side-steps the need for the survey system to identify the presence of line-marking, and simply requires it to assess the condition of the line-marking.

6.5.3 FOI Identification

The problem of failing to correctly determine if a candidate FOI is indeed a double line is again believed to be due to departures from the ideal survey condition of good diffuse ambient light. However, wet weather, complex pavement surface conditions and different line-marking line widths also play roles in causing the problem.

Figure 6.18 shows an example of a survey image along a section of the Lake Highway, where strong direct light on a wet road surface resulted in glare from the pavement adjacent to the line-marking, causing the basic survey system to mis-identify the line-marking type as "other line type".

Figure 6.18: Strong light at Lake Highway

Before seeking to address this problem in an extended survey system, it is worth noting that the inability of a basic survey system to correctly identify line-marking of a wet pavement under sunny conditions may be indicative of problems faced by drivers under such conditions.

Feature identification can also be influenced by complex images, such as result from other vehicles, shadows, line-marking at intersections, and objects such as railway lines. For example, problems occurred when the basic survey system assessed a section of the Lyell Highway crossed by a railway line, as shown in Figure 6.19.

Another example of a problem is shown in Figure 6.20, where uncertainties occurred due the presence of tyre wear lines parallel and adjacent to the centreline-marking. This led to the incorrect identification of the double line-marking by the basic survey system as "other line type".

Finally, on one section of the Lake Highway, several excessively broad single lines were mis-identified as double lines because they are wider than the pre-defined width limit (Section 6.3.3). This problem could be solved either by changing the pre-defined width limit, or by using another neural network to identify the line pattern.

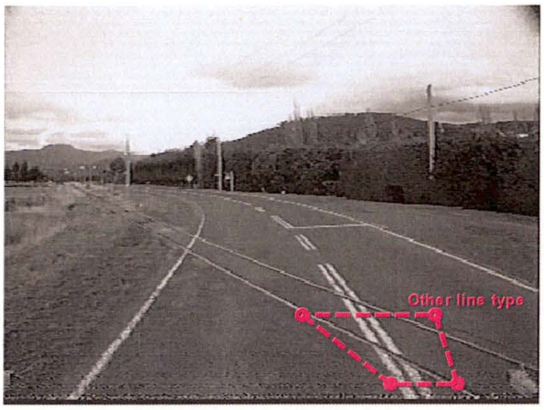


Figure 6.19: Survey passed through a railway at Lyell Highway

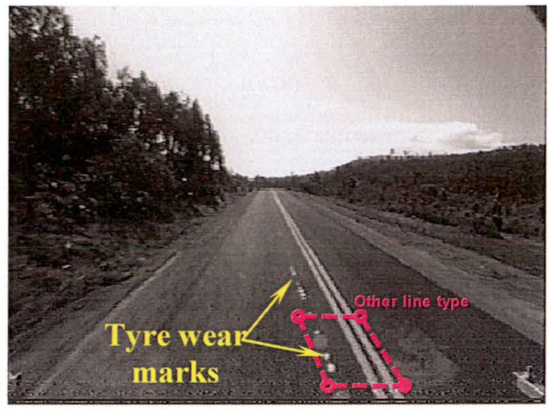


Figure 6.20: Feature identification process interrupted by tyre wear lines

6.5.4 Condition Assessment

The basic survey system neural network trained for line-marking condition assessment was found to be unreliable when applied to certain images. This was due to the images being different from those used to train the neural network

The neural network performed particularly poorly along the Gordon River Main Road, since the survey was conducted under lower than ideal ambient light levels, as shown in Figure 6.21. In addition to light levels, any highway property relied on by a neural network to assess line-marking condition has the potential to influence the assessment result, and such properties include pavement seal, colour, and shadow effects from roadside vegetation.

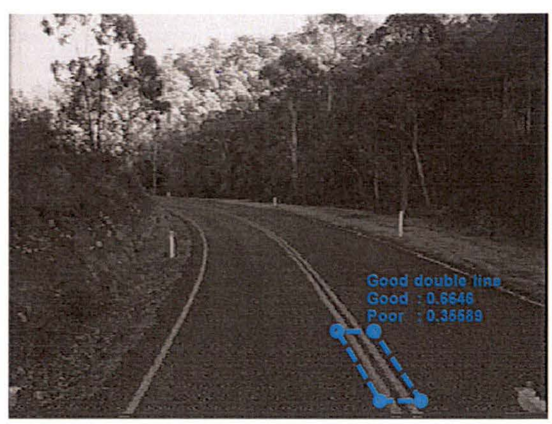


Figure 6.21: Uncertainties under overcast sky at Gordon River Main Road

These problems can all be addressed by an extended survey system, but with the caveat to Keep Things Simple. A neural network trained on too wide a range of images will tend not to work as well as multiple neural networks used in a staged approach, one of the biomimicry-inspired survey design application principles discussed in Chapter 4. A variation on this is that it might be better to develop different versions of an extended survey system for application to different highways, since survey conditions are clearly quite different for highways such as the Midlands Highway and the Gordon River Main Road.

6.6 Basic System Software

6.6.1 System Test Mode

Figure 6.22 provides an overview of the software developed by the author for the basic centreline-marking survey system while in test mode.

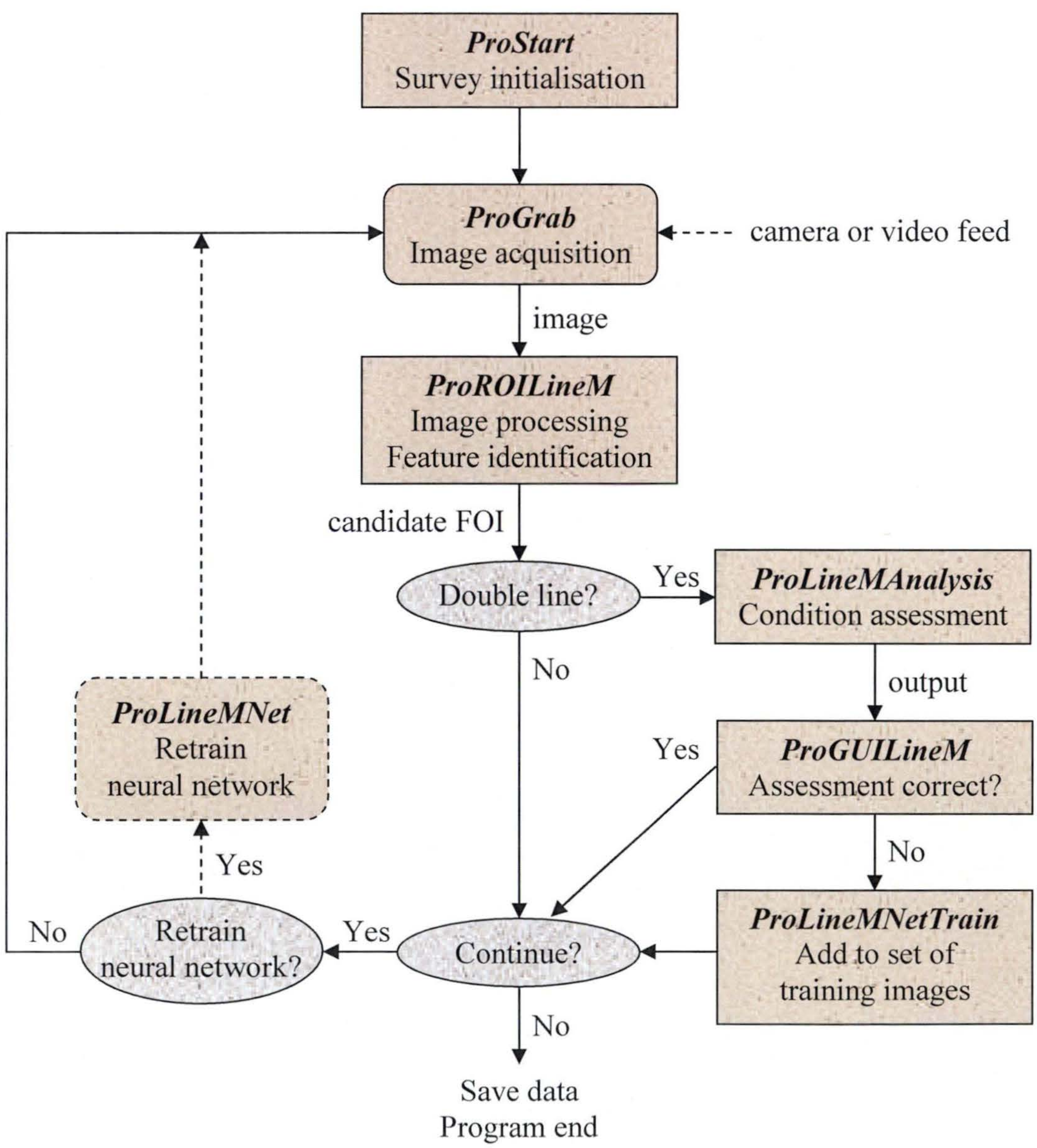


Figure 6.22: Basic survey system test mode software overview

As the generic system design is highly modular, the software is similar to the guidepost survey system software in the previous case study. The system is initialised by *ProStart*, and the principal software routines are *ProGrab* (image acquisition), *ProROILineM* (image processing and feature identification), and *ProLineMAnalysis* (condition assessment). The follow-on analysis module was not incorporated into the survey system, but to do so would be a straightforward task.

ProStart establishes the ActiveX control of the video card driver in preparation for grabbing images from the camera or from archived video feed. It also contains a "Grab" menu button to allow the user to start the survey at a specific time/location.

ProGrab is called by *ProStart* once the "Grab" button is pushed. It grabs images, which are directed to *ProROILineM*.

ProROILineM defines the ROI for centreline-marking, and identifies the candidate FOI via image processing techniques, including thresholding; and dilation to connect line-marking pixels. It identifies the line type based on the width of the candidate FOI. If the double line-marking FOI is confirmed, the image is rotated and resized into a standard form, and directed to *ProLineMAnalysis* as neural network input (for condition assessment).

ProLineMAnalysis is called by *ProROILineM*. It uses a neural network to identify the condition of the input line-marking as either good or bad. It also examines the level of confidence of each output.

In survey system test mode, once the condition of an FOI is assessed by *ProLineMAnalysis*, the user is prompted by *ProGUILineM* to confirm the assessment. If the assessment (*Good* or *Poor*) is either incorrect, or is correct but with a low level of confidence, the line-marking image is added to the neural network training set by *ProLineMNetTrain*. The neural network is retrained by *ProLineMNet* from time to time in light of the new additions to its training data.

The entire image grabbing and analysis process takes less than 0.5 second for each image (and incorporation of the follow-on analysis module would not change this). After each image analysis, *ProStart* asks if the user wants to continue to analyse the next image, retrain the neural network, or quit the program.

6.6.2 System Operating Mode

Figure 6.23 provides an overview of the software developed for the basic line-marking condition assessment system in operating mode.

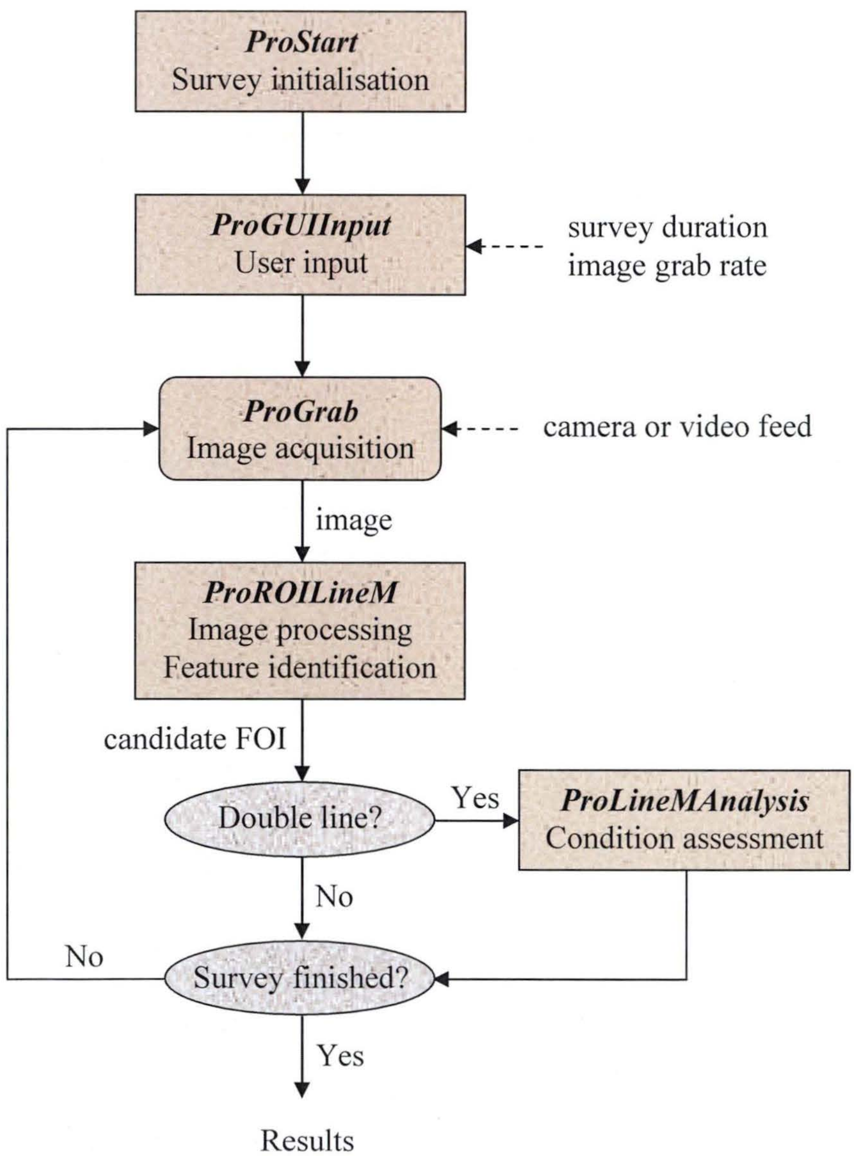


Figure 6.23: Basic survey system operating software overview

The programming routines for system operating mode are slightly different to those used in the survey test mode. They include an additional GUI routine, *ProGUIInput*, which prompts the user to specify the total survey duration and image grab rate. In addition, *ProStart* also examines the overall line-marking condition along the survey road section, and the overall level of confidence.

6.7 Summary

This chapter has presented a basic centreline-marking survey system developed from the generic system design approach set out in Chapter 4. Image processing techniques were again merged with artificial intelligence tools for feature identification and condition assessment, with a neural network similar to that used for guidepost identification established for line-marking condition analysis. A similar approach can be used for surveys of other line types, such as edge lines or single solid lines.

The performance of the basic survey system was found to be good (~92%) under ideal survey conditions, confirming that it incorporates the essential aspects required of a survey system for this particular application. The basic survey system's performance dropped to ~70% under non-ideal survey conditions. The reasons for the poor performance were examined, and provide a platform for the development of an extended survey system able to handle more challenging highway surveys.

A demonstration follow-on analysis was carried out to take into consideration horizontal road alignment in the line-marking survey, using an expert system. This expert system adjusts the line-marking condition assessment results with greater maintenance priority given to poor condition lines on a road bend than on a straight section of highway.

Such context-based expert systems can be used to consider multiple aspects of context, such as posted speed limit, and can be used to aggregate assessment results into bulk condition indices for at-a-glance use by decision makers.

7.0 EXTENDED SURVEY SYSTEMS

7.1 The Need for Extended Survey Systems

This thesis has argued that instead of seeking to provide a single road survey system for multiple applications, survey systems should instead be developed for specific applications from a generic system design.

A related barrier to developing an automated survey system is how to ensure that it maintains good performance under changing survey conditions. This thesis has proposed that a staged approach to survey system development can solve this problem. In the first stage, the application of the generic design approach described in Chapter 4 to specific road feature surveys leads to the development of a *basic* survey system, and case studies of this process have been presented in Chapter 5 (guidepost counting) and Chapter 6 (line-marking condition assessment). A basic system works well for the ideal survey conditions under which the system was trained. It is a baseline system that establishes the fundamental aspects of a system suitable for the application.

When the survey conditions are changing, such that they sometimes vary significantly from ideal survey conditions, then a basic system is not expected to work well. Examining the performance of a basic system under such conditions leads to identification of the requirements for an *extended* survey system. Such examinations were carried out at the conclusion of each case study.

This chapter sets out the extended survey system development strategy, and discusses the tools needed to implement the strategy. It illustrates the methodology through the development of an extended guidepost survey system, with the caveat that more than one extended survey system might sometimes be required for actual highway survey conditions that vary in different ways from ideal conditions, as shown in Figure 7.1. The chapter concludes by presenting the results of a 50 km field test of the extended guidepost survey system.

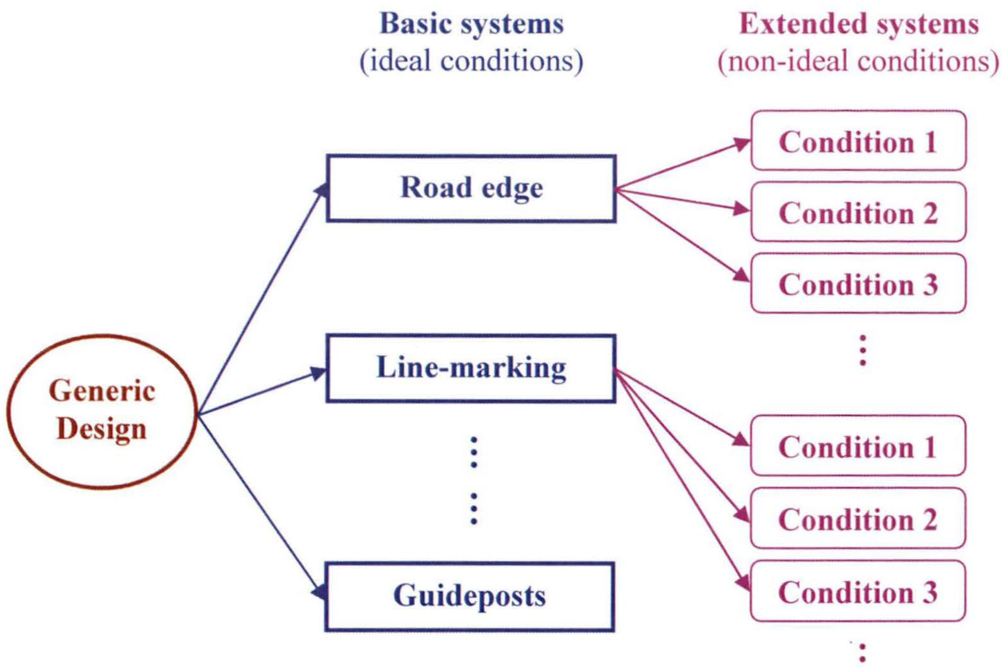


Figure 7.1: Different versions of an extended survey system may be needed for different survey routes and conditions

Survey conditions can be described by a combination of survey parameters and road environment. Survey parameters include the survey vehicle speed; weather conditions (see Figure 7.2); and vibration due to poor road surface condition.

Figure 7.2: An extended system may be needed to address dark and/or shadow conditions

Some survey parameters can be controlled to suit the survey system. For example, if a basic survey system is associated with good weather conditions, then operating the survey system under poor weather conditions or at night should be avoided.

Occasionally, maintaining a specific survey parameter at the required condition can be difficult, the survey vehicle speed providing an obvious example. In addition, the road alignment and roadside environment cannot be controlled during the survey, and can be expected to change in the course of any highway survey that is reasonably long, as is required in practice. The goal of developing an extended survey system is that it should perform well under such changing conditions.

7.2 Extended System Design

7.2.1 Design Overview

Figure 7.3 summarises the extended survey system design process, based on an examination of the factors responsible for a basic survey system's performance problems under non-ideal survey conditions.

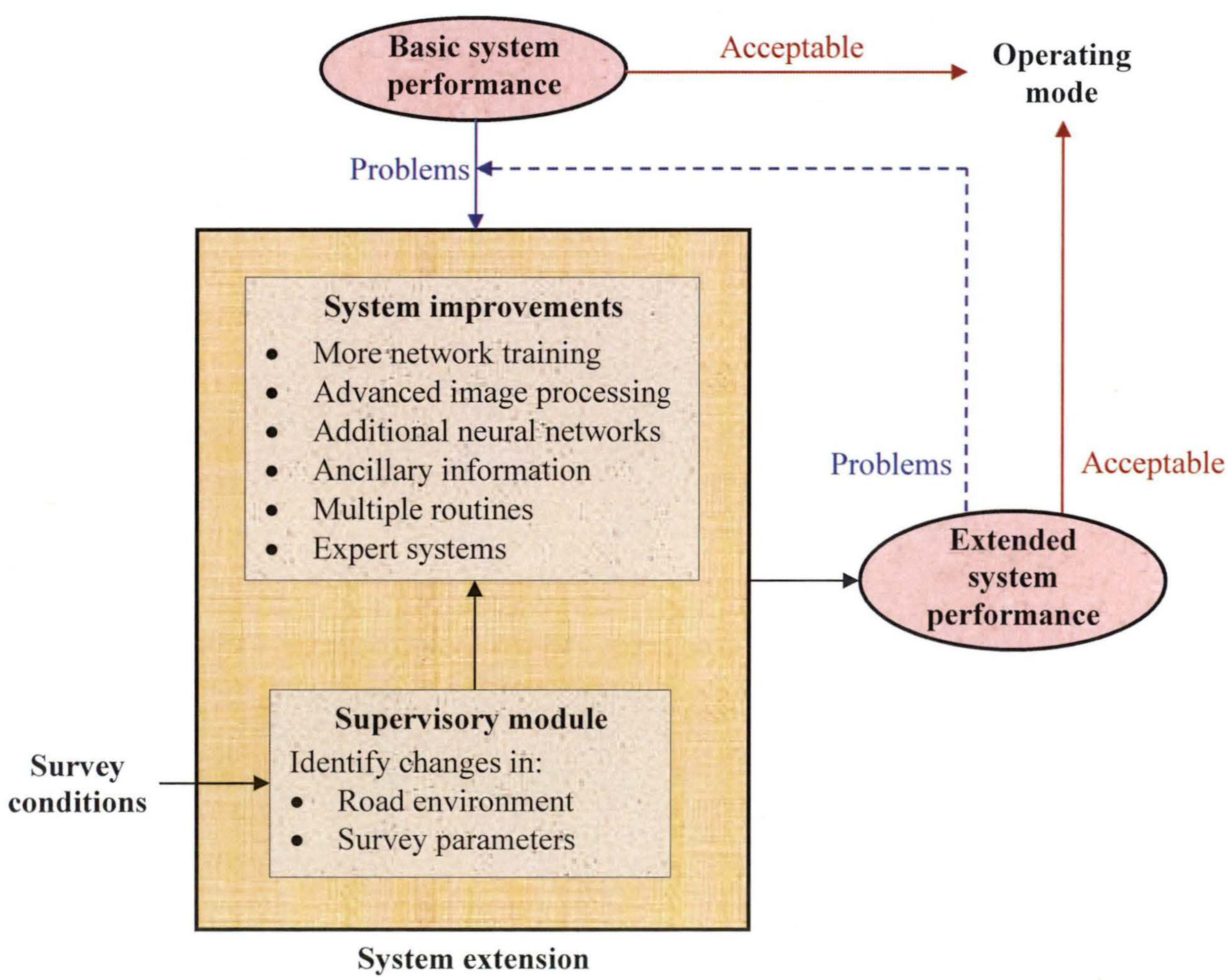


Figure 7.3: Extended survey system design overview

An extended survey system can attempt to deal with non-ideal survey conditions by modifying the software routines developed for the basic system, and various survey improvement methods are listed in Figure 7.3. However, if the survey conditions are not simply different from ideal conditions, but also change during the course of a survey, then this triggers the need to establish a supervisory module to identify the changes and implement appropriate system extension routines to maintain good survey performance under the new conditions.

7.2.2 System Improvement Tools

More network training. A neural network that performs adequately in a basic survey system may simply require additional training in order to perform well under extended survey system conditions. This can be done by running the extended survey system in test mode to gather additional training images as appropriate, and then retraining the neural network.

Advanced image processing. One motivation for proposing a staged approach to survey system development, discussed in Chapter 4, was recognition that image processing methods tend to divide into basic tools that almost any survey system will need, and more advanced tools such as deblurring and noise filtering. The more advanced tools are appropriate for extended systems.

Additional neural networks. Certain non-ideal survey conditions may require additional neural networks to be incorporated into the extended survey system. For example, additional neural networks would be needed for a roadside vegetation survey in which the non-ideal conditions involve a more complex mosaic of vegetation types.

Ancillary information. Ancillary information can be used to assist identification of candidate Features of Interest (FOIs), and the assessment of such FOIs. An example given in Section 4.3.5 is the use of a colour frequency distribution to help identify a road sign.

Multiple routines. Multiple image processing routines or neural networks may be required to handle a changing survey condition. Such new routines do not necessarily require advanced techniques, but are associated with a supervisory module implementing a survey condition classification scheme (e.g. shadows versus no shadows, or dry weather versus rain), and selecting an appropriate routine to handle each classification.

The design philosophy of selecting one of a number of routines avoids creating a single overly complicated image processing routine, and avoids the known risk of poor performance by a neural network that is trained to respond to too broad a range of conditions. This approach is taken in the case study presented later in this chapter (Section 7.3), in which ambient light level (pixel intensities) is classified into three categories, and the choice of filter for image processing, and the choice of neural network, depend on which category applies to a given image.

Expert systems. Expert systems are decision-making tools, and can help in tasks in which more than one variable may influence a decision. For example, the health of roadside vegetation is broadly assessed in terms of the width of the road reserve, the condition of native vegetation, the extent of weed species, and whether young vegetation is present (NSW REC, 1995). An expert system is ideally suited to combining such information into a roadside vegetation index.

7.2.3 Supervisory Module

Establishing a supervisory module qualifies as biomimicry, for the supervisory aspect to monitoring the business-as-usual work of a person is well known. It is common experience that the mind does not pay full attention to the details of routine tasks, such as walking city streets, or driving along a highway, and yet it alerts a person when something unusual happens. This is the basis of the so-called sixth sense, which is no more than the supervisory aspect of person's mind warning the conscious mind of danger.

The key goal of a road survey system's supervisory module is that it be able to identify changes in survey conditions, and take action as appropriate to modify the survey system's procedures to address the changing conditions. In considering how best to approach this exercise, a review of the state-of-the-art in supervisory system engineering was undertaken.

Appendix D reviews the development and applications of supervisory systems in various fields, such as unmanned aerial vehicles (Clough, 2005; DTIC, 1998; Godbole et al., 2000) and deep sea exploration robots (Labbé et al., 2003; von Buchstab, 2005), robotics control, and manufacturing processes. Such systems are also useful in modelling applications where high level automated decision-making is needed to supervise process behavior. Advanced techniques in artificial intelligence are also becoming better known, such as reinforcement system learning and adaptive neural networks, as reviewed in Appendix E, based on the idea of allowing the environment to control and adapt the system during a feature survey.

However, a well established engineering principle is to keep things simple if possible. In an extended road feature survey system, the author believes that it should usually be possible to produce a satisfactory supervisory module using the same image processing and neural network tools that are already used in basic survey system work. For example, a difference in ambient light level can be monitored by a pixel intensity histogram, as shown in Figure 7.4.

7.2.4 System Testing

Figure 7.3 shows that, unsurprisingly, developing an extended survey system with acceptable performance is an iterative process, requiring the system to be tested ahead of field trials. This is the approach taken to the case study presented in this chapter. As noted, different rural highways may require slightly different extended survey systems, and a survey system whose performance is good on one highway should not be assumed to work well on another highway.

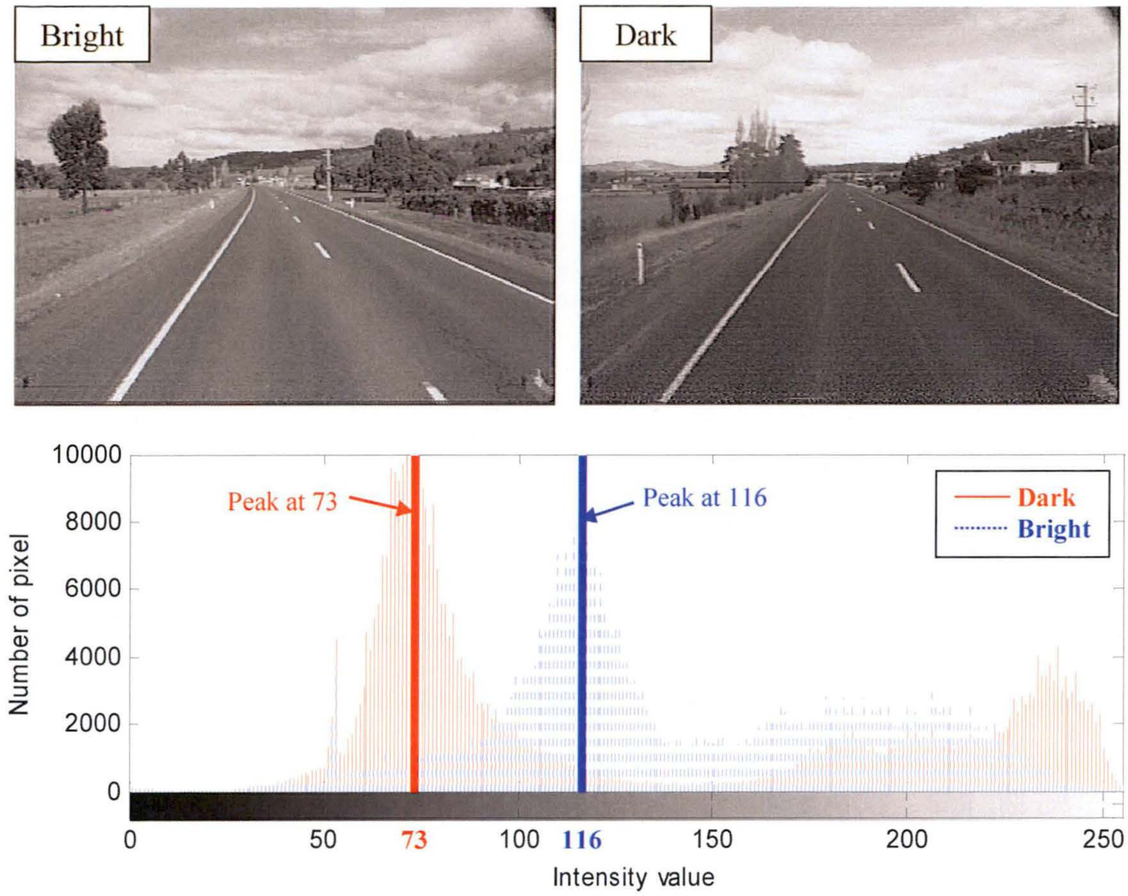


Figure 7.4: Greyscale intensity histograms of bright and dark images

7.3 Case Study: Guidepost Counting

7.3.1 Extended System Design

The assessment of the basic guidepost survey system's performance under non-ideal survey conditions was set out in Section 5.4.1. Problems identifying candidate Features of Interest (FOIs) and assessing the candidate FOIs, appeared both largely to be caused by changing ambient light conditions, and these problems are addressed by this case study.

Another problem was that the Region of Interest (ROI) in an image occasionally failed to capture a guidepost, and the survey vehicle had passed by the guidepost at the time of grabbing the next image. This problem is addressed by defining a new ROI for the field survey version of the guidepost survey system, presented later in this chapter (Section 7.4), which uses a camera with a different and better orientation than that used for the archived survey footage used to date.

Figure 7.5 shows the extended system design, and this can be compared to the generic design presented in Figure 7.3. In brief, the system extensions are to:

a) establish a supervisory module to monitor light conditions;

b) use an appropriate non-fixed binary threshold value for the first filtering operation, as described in Section 5.2.2; and to

c) establish a selection of neural networks to assess candidate FOIs, the choice of neural network depending on the light condition.

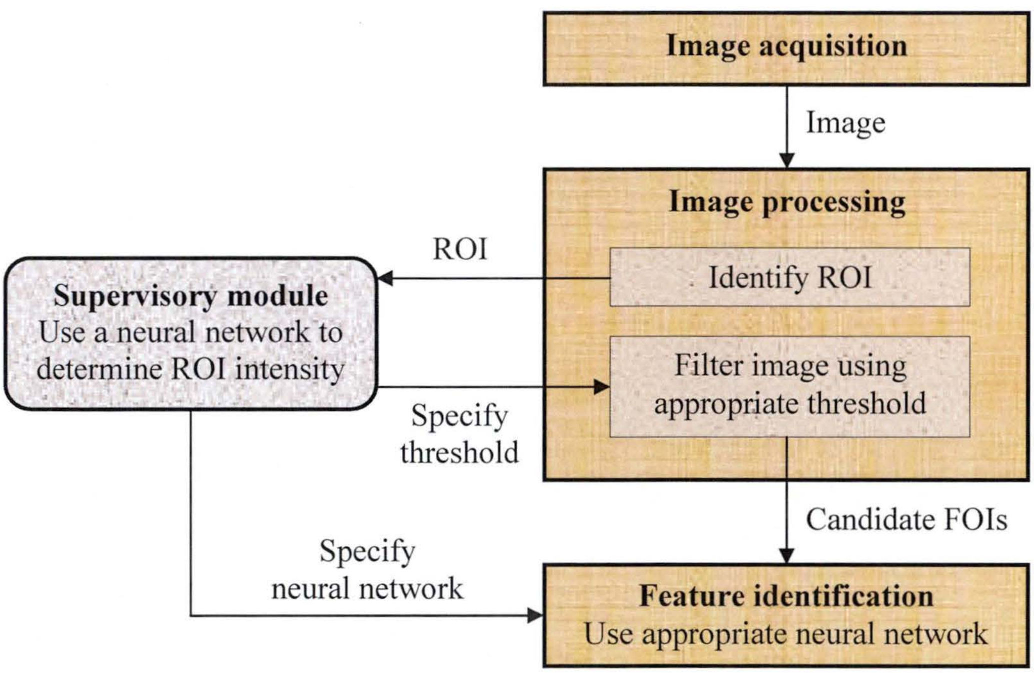


Figure 7.5: Extended guidepost counting survey system

Supervisory module

The supervisory module for this extended survey system is chosen to be a neural network that is trained to examine the ambient light condition and select an appropriate binary threshold for image processing, and to select an appropriate neural network for candidate FOI identification.

The supervisory neural network's architecture has 3 layers of neurons, with 20 neurons using log-sigmoid transfer functions in the input and the hidden layer, and a single neuron with a pure-linear transfer function in the output layer. It is designed to receive an entire ROI image resized to a standard $100 \times 100 = 10{,}000$ pixel greyscale input data. The neural network is trained to produce an output value that lies between 0 and 1 that is the appropriate binary threshold for the first image filtering operation in the exercise to determine candidate FOIs in the ROI. Appropriate threshold values for the set of training images were determined empirically.

Threshold filtering operation

Figure 7.6 illustrates the problem identified in the study of the basic guidepost survey system's performance under the non-ideal survey condition of changing light levels, as discussed in Section 5.4.3: filtering an image using a fixed binary threshold to find bright objects does not work well if the ambient light is diffuse but weak, or if the light is direct and such that the front of the guidepost lies in shadow.

The basic survey system used a fixed threshold of 0.75 ($\approx$192 greyscale), and a typical example of successful image filtering under ideal light conditions is shown in the top plot of Figure 7.6. In the middle plot of Figure 7.6, the guidepost is not clearly identified as a candidate FOI by a threshold of 0.75, since many background pixels are brighter than the threshold. These pixels all become white pixels in the filtered binary image, which leads to difficulty in identifying the guidepost object as a candidate FOI. The higher threshold of 0.9 ($\approx$230 greyscale) works better for this situation.

Conversely, in the bottom plot of Figure 7.6, the guidepost is not clearly identified as a candidate FOI by a threshold of 0.75, since most guidepost pixels have lower intensities than 192, and filtering will convert them to black pixels in the binary image. The lower threshold ($0.5\approx128$ greyscale) works better for this situation.

Figure 7.6: Identification of candidate FOIs under different intensity contrast conditions

Candidate FOI assessment

The supervisory module's output is used to classify the light condition as:

Dark	$0.00 \leq \text{Threshold} < 0.60$
Normal	$0.60 \leq \text{Threshold} < 0.85$
Bright	$0.85 \leq \text{Threshold} \leq 1.00$

where thresholds of 0.6 and 0.85 correspond to greyscale intensities of 153 and 217 respectively.

Three neural networks were developed and trained to recognise guideposts under *Dark*, *Normal* and *Bright* conditions. The architectures of these neural networks are identical to the neural network used by the basic system for guidepost identification, but trained under the different ambient light conditions. The selection of the appropriate neural network module for use under each specific condition is decided by the supervisory module based on the light level classification for each ROI.

7.3.2 Extended System Performance

The basic survey system's performance under ideal survey conditions, on selected sections of the Midland Highway and the Mole Creek Main Road, was examined in Chapter 5, and found to be 83%. The performance of the extended survey system on the same sections is 90%, with a confidence level of 82%. Under non-ideal survey conditions associated with other sections of these two rural highways, the overall basic system performance's was found to be 54% (see Table 5.3). The extended survey system's performance under the same non-ideal conditions is set out in Table 7.1, and the overall performance level of 72% with a confidence level of 79%, clearly a significant improvement.

Road	Test	Actual posts	Correct count	System Performance	Confidence level
MH	1	13	11	85%	72%
MH	2	22	20	91%	73%
MH	3	14	11	79%	73%
MH	4	36	27	75%	71%
MH	5	23	15	65%	85%
MC	1	19	9	47%	84%
MC	2	20	15	75%	85%
MC	3	19	10	53%	83%
MC	4	17	13	76%	91%
MC	5	13	11	85%	71%
Overall		196	142	72%	79%

Table 7.1: Extended system performance under non-ideal conditions along the Midland Highway (MH) and the Mole Creek Main Road (MC)

In Table 7.1, the extended survey system performance is generally good, but on two sections of the Mole Creek Main Road the performance is below 60%. The reason for this is that light levels (i.e. intensity contrasts) are too low to allow effective system performance, a point discussed in Chapter 5 (see Figure 5.19).

Figure 7.7 compares the performances of the basic and extended survey systems under non-ideal survey conditions.

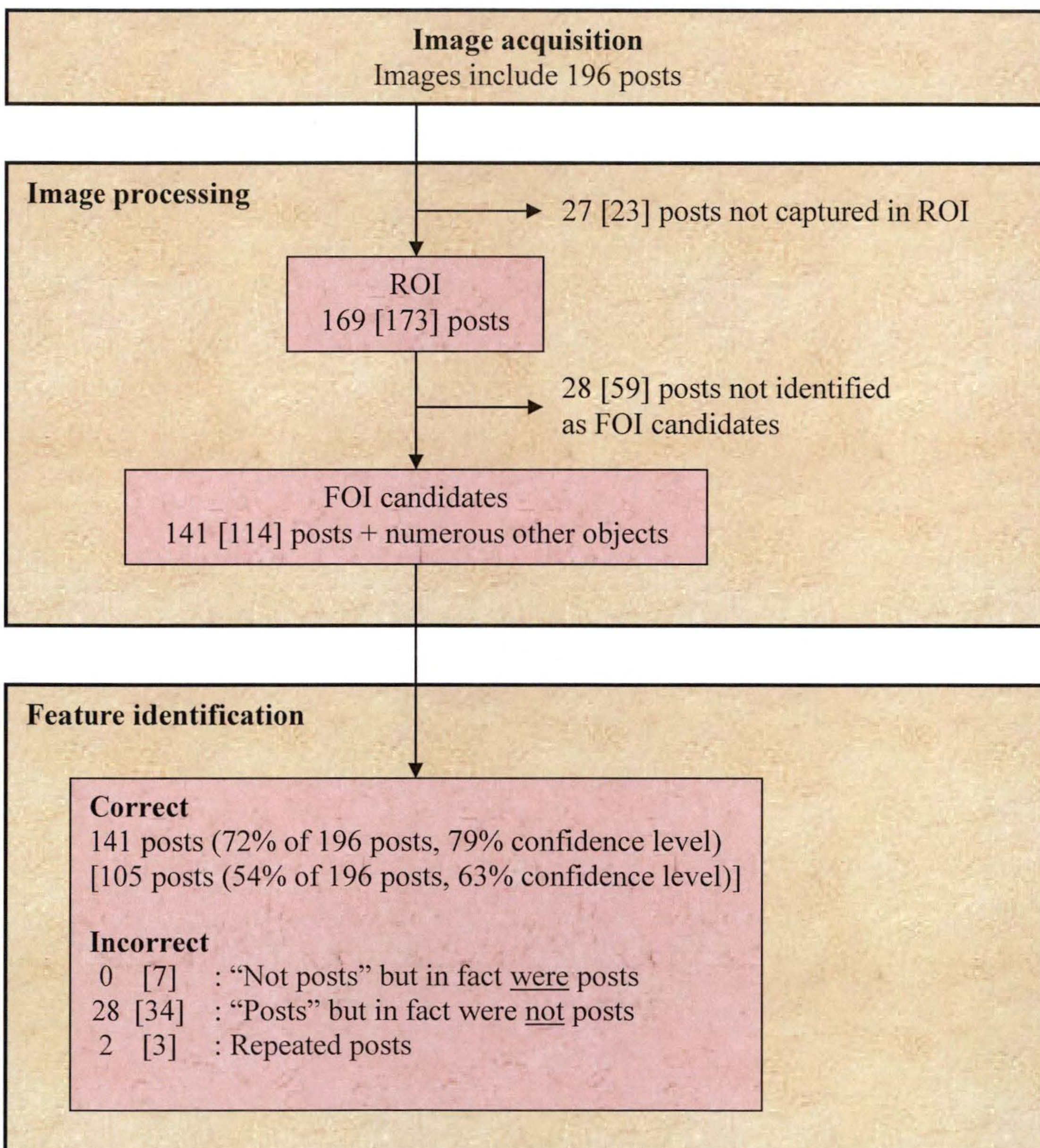


Figure 7.7: Comparison of the extended survey system's performance to the basic survey system's performance [in square brackets]

Table 7.2 reviews the problem areas identified in Section 5.4, and shows significant improvement in the two problem areas targeted by the extended system. The number of guideposts included in image ROIs, but not identified by the image processing procedures as candidate FOIs within the ROIs, has halved, while the number of mis-identifications of candidate FOIs by the FOI identification procedure has also improved.

	Extended system	**Basic system**
Missed or repeated guideposts		
• Posts not included in the ROI of an image, and not presented in the next image	27	23
• Posts appearing in the ROIs of two consecutive image grabs	2	3
Candidate FOIs		
• Posts included in image ROIs, but not identified by the image processing procedures as candidate FOIs within the ROIs	28	59
FOI identification		
• FOIs mis-identified by the FOI identification neural network	28	41

Table 7.2: Comparison of problem areas for basic and extended guidepost survey systems under non-ideal conditions (Total guideposts = 196)

The only problem area in which no improvement was made is the number of posts not included in the ROI of an image, and not presented in the next image. The slight difference in numbers for the two survey systems simply reflects slightly different survey start and end locations on the test sections of highway. As noted above, this version of the extended survey system did not attempt to remedy this problem, but was successfully corrected in the extended survey system version used for the long (50 km) survey, presented in the next section.

7.4 50 km Highway Survey

7.4.1 Survey Description

This section presents the results of a field trial to examine the performance of the extended guidepost survey system when applied to the kind of rural highway distance of interest to asset managers.

The survey was carried out by the author along the Midland Highway in Tasmania on 25 April 2006, using the vehicle shown in Figure 7.8. The survey covered about 50 km of highway between Oatlands and Ross, as shown in Figure 7.9, and targeted guideposts along the west side (i.e. the nearside) of the road. Figure 7.10 shows typical views of the highway along the survey route. The survey covered many kilometers of highway that are considered to represent non-ideal survey conditions, with changing road alignments, changing roadside environments, and changing – although generally good – ambient light conditions.

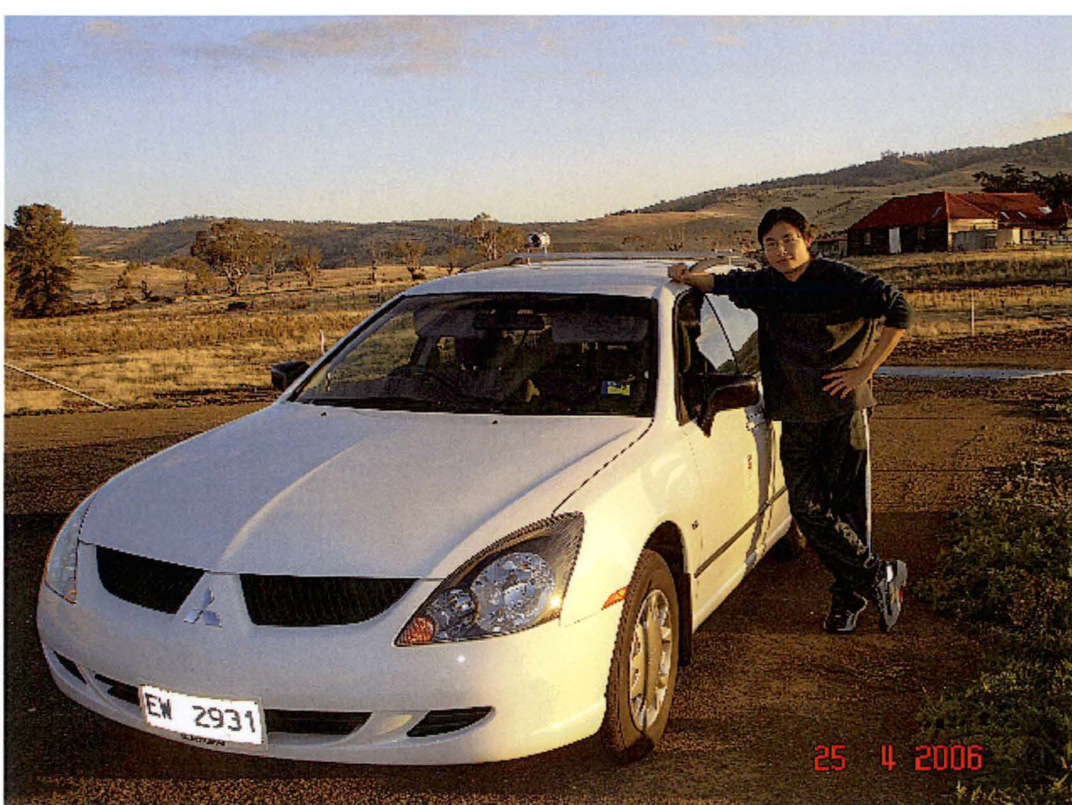


Figure 7.8: The author with the survey vehicle on the Midland Highway, Tasmania, on 25 April 2006

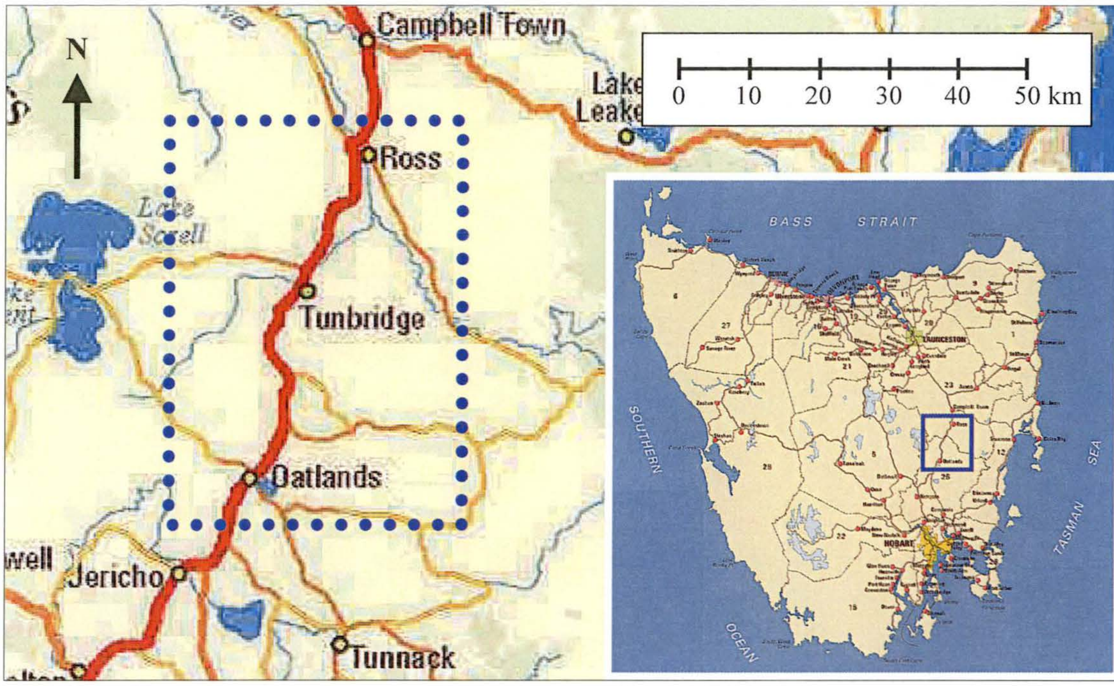


Figure 7.9: Map of survey coverage

Figure 7.10: Typical views of the Midland Highway survey route

7.4.2 Survey System Setup

Survey camera

The survey was carried out using a Panasonic NV-GS180GN digital video camera (MEI, 2006; PA, 2006), shown in Figure 7.11.

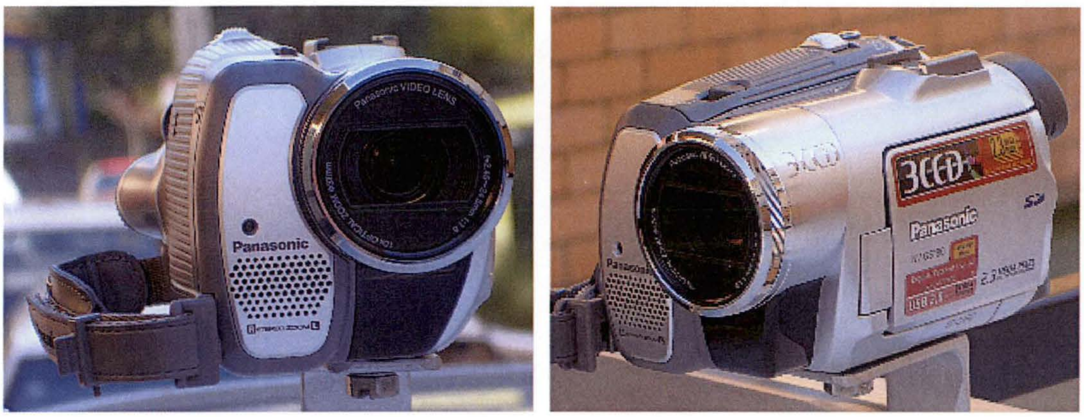


Figure 7.11: Panasonic NV-GS180GN video camera

The camera is an off-the-shelf model, which can be bought at a cost of about A$900 (in 2006). It has a focal length between 2.45 mm to 24.5 mm, and was mounted on the top of the vehicle during the survey, and operated by remote control.

The camera contains a 3 CCD image sensor for processing to avoid light loss (see Figure 7.12). Although greyscale images are used in the present guidepost survey system, the survey footage was recorded in RGB colour, in case future survey system refinements require the consideration of colour, perhaps as ancillary information. The camera also contains an image stabiliser function, to ensure better quality images when subject to vibration, an important consideration when the camera is attached to a survey vehicle.

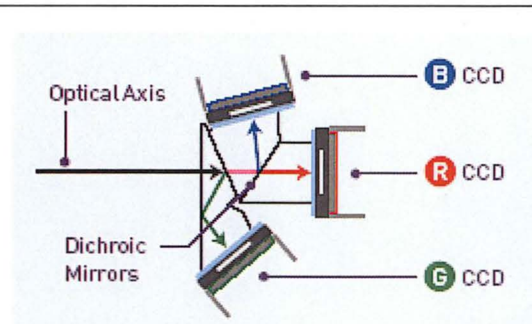


Figure 7.12: The 3 CCD system used in the video camera (PA, 2006)

Although it is more convenient to use a video camera that can record image data digitally on a mini-DVD or an internal hard drive, internal hard drives risk damage if the camera is subjected to strong vibration, and images recorded on the DVD or the hard drive could be lost. Therefore, it was decided to record the survey data on mini digital video cassettes. A digital video cassette can actually store better quality video than a DVD or a hard drive, since the data are stored without much compression.

A standard camera battery was used, which can last for about 1.5 hours of continuous usage. About 4 hours of usage can be achieved using a high performance battery. A standard digital cassette can record up to 80 minutes for short play and 120 minutes for long play. Live survey footage could be viewed on a laptop computer from within the survey vehicle, as described below; while recorded survey footage could be viewed on the camera's 2.5 inch LCD screen, in play-back mode, enabling its operation to be checked ahead of initiating the survey.

Survey vehicle

The survey vehicle was a University of Tasmania Mitsubishi Magna station wagon, shown in Figure 7.13. The purpose-built roof rack allowed the camera to be mounted on top of the vehicle.

Figure 7.13: A Mitsubishi Magna station wagon with roof rack used for survey

The vehicle has cruise control, which allowed the survey to be carried out at an near constant speed of 80 km/h.

The vehicle also has a good suspension system, as vibration is a major concern when filming from a survey vehicle. Vibration reduces the video quality and produces blurred survey images such as those shown in Figure 7.14. The vehicle suspension system, together with the camera's image stabiliser function, largely avoided problems due to vibration during the survey.

Figure 7.14: Survey images blurred by vibration

The survey camera was attached to the roof rack of the vehicle using a stainless steel cross bar, shown in Figure 7.15, fabricated at the University of Tasmania's School of Engineering workshop. The camera was attached to the bar via its standard tripod mounting (Figure 7.15 right). The setup was stable and secure, which reduced noise in the survey images as well as reducing the possibility of damaging the camera due to vibration shock during a survey.

Figure 7.15: Camera setup

Laptop computer

A Pentium IV laptop computer was used to view live survey video inside the survey vehicle, and hence confirm the camera's orientation. The camera feed was input to the laptop via its USB connection. Real-time surveys were not possible with this particular laptop due to battery life limitations, and instead the survey data were processed back at the University of Tasmania. In practice, survey data could be processed in real-time by just about any off-the-shelf computer with an appropriate "smart" video card, via S-Video output or an AV output interface, or through a USB connection. The MotionDV Studio software package, for example, enables video input from a Panasonic video camera to a computer via a USB connection.

Image grabbing and analysis

The basic and extended guidepost survey systems, described in Chapter 5 and earlier in this chapter respectively, were developed using Tasmanian State Government archived survey data, in which the camera height and orientation were different from the April 2006 survey. Therefore, a new guidepost ROI was defined, as shown in Figure 7.16, appropriate to the new camera setting. The new ROI was a 300 × 350 region with coordinates (201:550, 101:400) of the grabbed 576 × 768 pixel image.

Figure 7.16: Left - Previous camera view and ROI
Right - New camera view and ROI

Fifty highway images, taken using the new camera orientation and ROI, were used to train the supervisory module neural network for ambient light level identification, and the three neural networks for feature identification under different light conditions. This exercise was straightforward given the high degree of automation and modularity in the survey system software.

7.4.3 Survey System Performance

The extended survey system's performance on the ~50 km survey is summarised in Figure 7.17. The overall performance was 88%, with a 72% level of confidence, which is pleasing given that this was the first long distance field trial undertaken.

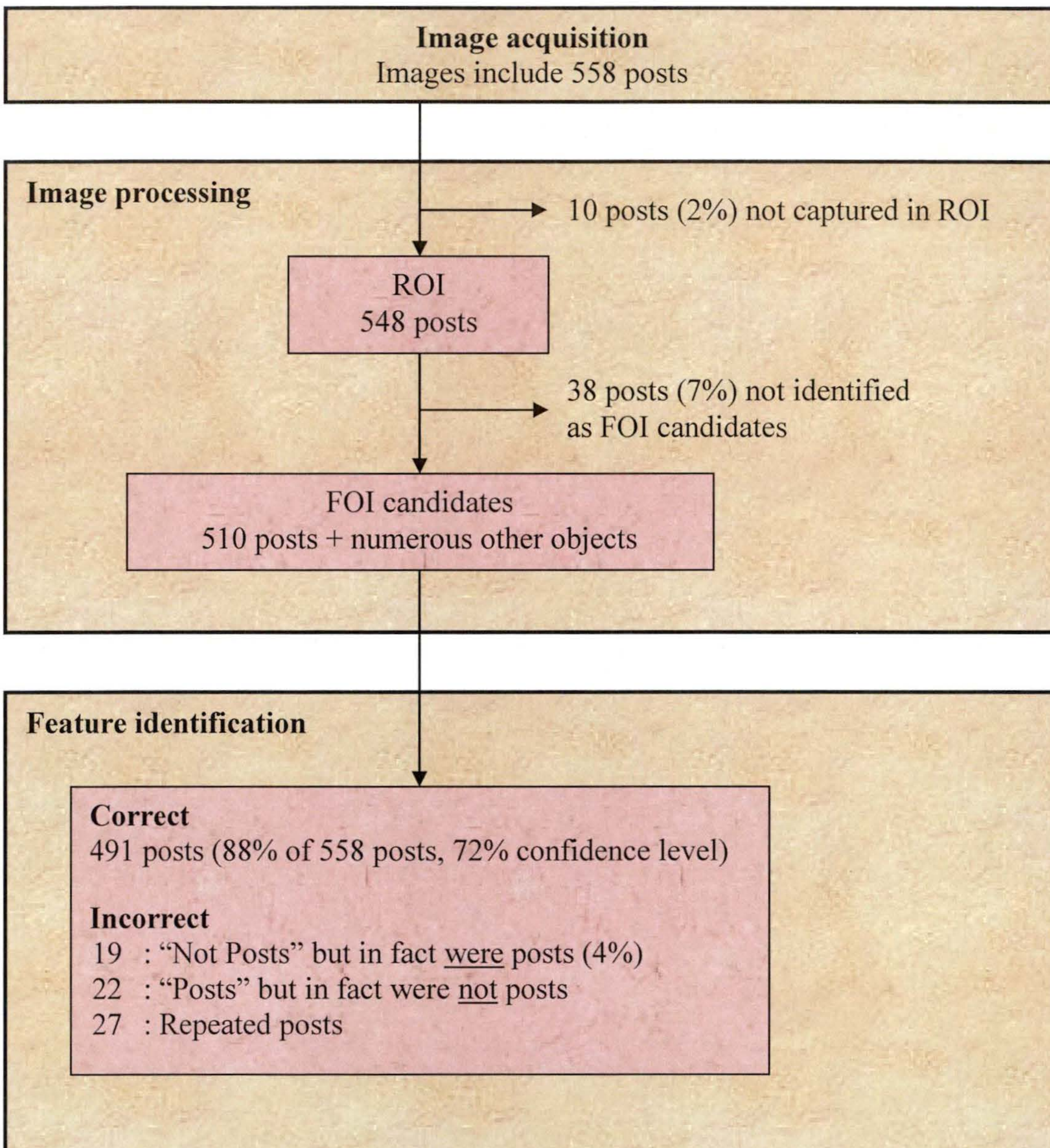


Figure 7.17: System performance overview

Table 7.3 summarises the problem areas, and it can be seen that the main improvement, with respect to the performance of the previous version of the extended survey system, is that the new ROI does a better job of correctly capturing guideposts. Only a very few guideposts were either missed by consecutive images, and hence not counted, or were present in consecutive images, and hence double-counted.

Missed or repeated guideposts	
• Posts not included in the ROI of an image, and not presented in the next image	10
• Posts appearing in the ROIs of two consecutive image grabs	27
Candidate FOIs	
• Posts included in image ROIs, but not identified by the image processing procedures as candidate FOIs within the ROIs	38
FOI identification	
• FOIs mis-identified by the FOI identification neural network	41

Table 7.3: Review of problem areas (Total guideposts = 558)

Additional refinements to the extended guidepost survey system would enable it to perform well on rural highway surveys involving different guidepost types, spacing, or roadside environments. However, the potential of the present survey system to provide credible, repeatable results is clear. One obvious application of this survey system is to carry out repeated surveys of a specific section of highway at intervals of, say, six months, to establish an asset degradation curve.

7.5 Summary

The chapter has set out the general approach to developing an extended survey system, which may require establishing a supervisory module to monitor changing survey conditions and select survey system procedure options as appropriate. An extended guidepost counting survey system is developed to deal with changing ambient light conditions, and its satisfactory performance under non-ideal conditions on the Midland Highway and Mole Creek Main Road in Tasmania confirmed.

A 50 km Midland Highway field trial of the extended guidepost survey system is then presented, and its performance demonstrated to be very good. The field trial was carried out by the author on a section of the national highway in Tasmania, and involved custom mounting a camera on a University of Tasmania vehicle.

It is a straightforward task to develop an alternative versions of a given extended survey systems to handle rural highway surveys that depart in different ways from the ideal survey conditions associated with the basic survey system. For example, an extended survey system for application to a rural highway with different types of guideposts or different roadside environments (e.g. the deserts of an outback highway versus the grassy plains of the Midland Highway) would require retraining of the neural networks.

8.0 RESEARCH SUMMARY AND FOLLOW-ON WORK

8.1 Research Summary

Road feature and condition surveys are keystones of an effective road asset management system. However, traditional manual inspection methods are often subjective and expensive, and there is obvious motivation to automate the surveys to either replace or at least complement manual methods. To this end, significant progress has been made in supporting manual surveys with GIS/GPS technology, digital imagery, and survey databases supported by user-friendly interfaces.

Nevertheless, these efforts have stopped short of producing an automated road survey systems, although off-the-shelf computer hardware and software packages have been available for some years, with the clear potential to automate road surveys and carry them out in real time, if need be. This research was motivated by a desire to understand why this is so, and to explore the way forward.

Chapter 2 started the research by reviewing the nature and requirements of road feature and condition surveys and present survey methods, focusing on rural highway applications rather than urban road surveys. The key finding was that no single survey system (other than a human expert) can be flexible enough to cater for all survey needs. The first problem is the number of possible survey targets. There are fundamental differences between undertaking surveys of, say, signposts, line-marking condition, and roadside vegetation. A second problem is that of maintaining good survey system performance over rural highway survey distances measured in tens and often hundreds of kilometers.

Nature has faced and solved a similar problem in its efforts to fill very different and specific ecological niches. Biomimicry suggests that a way forward might be to identify a generic system design, rather than seek to develop a single do-all survey system. This is inspired by, for example, the quadruped design, which forms the basis for producing a wide range of animals such as giraffes, tigers, and mice, each suited for a specific ecological niche.

Chapter 3 reviews the state-of-the-art in image processing and artificial intelligence (notably neural networks and expert systems) software tools. It was concluded that these techniques can be divided into those methods that almost any road survey system will need to apply, and supplementary advanced methods. For example, image manipulation methods and feed-forward neural networks fall into the category of common tools, while deblurring methods and adaptive learning artificial intelligence techniques are more advanced methods.

Chapter 4 proposes a generic design approach to developing automated road feature and condition survey systems. The generic design is inspired by biomimicry, notably consideration of the human approach to carrying out road surveys. The three principal system components were identified to be:

1. Image acquisition, which mimics the work of the eyes in collecting visual information.

2. Image processing that parallels the work of the visual cortex in processing images. A Region of Interest appropriate to the road Feature of Interest (FOI) is windowed out from the overall image, and candidate FOIs are isolated.

3. Feature recognition and condition assessment that mimic the cognitive aspects of a human brain, notably its biological neural networks. This design component is usually associated with neural networks, which are powerful pattern/feature recognition tools, and here are used to determine which candidate FOIs are actual FOIs, and then to assess the condition of the FOIs if necessary.

Any necessary follow-on analysis of the survey results constitutes a fourth system component. This often involves consideration of context (such as horizontal alignment, or posted speed limit), and/or aggregation of information into overall indicators of the condition of a road feature over a length of highway. Expert rule systems are ideally suited to such tasks, which are essentially decision-making exercises.

Examining the operation of the human visual information processing system also leads to the identification of principles to guide the application of the generic system design to produce surveys of a given road feature. The principles identified by the research were:

(i) Apply biomimicry tools
(ii) Use a modular approach
(iii) Use a staged approach to analysis
(iv) Use ancillary information where available and appropriate
(v) Develop clear performance criteria

The Matlab technical computing package was chosen for the present research. Matlab is excellent at processing data arrays, such as images, and has good image processing, neural network, and expert rule system "toolboxes". Data acquisition was accomplished by a Picolo video card, controlled by Matlab through an ActiveX interface, and supported by an extensive library of interface commands. These commands include capabilities not examined by this research, such as computer-controlled camera zooming and feature tracking.

A key feature of the generic design approach, which fits well with the review of image processing techniques and artificial intelligence tools, is that the development of an automated road survey system is best carried out in two distinct stages.

The first stage is to develop a *basic* survey system which performs well under ideal survey conditions, with the goal of understanding and establishing the fundamental aspects of the survey system without the clutter of the software procedures that will be needed to address secondary performance aspects of the survey systems.

The second stage is to develop an *extended* survey system that can handle the more complex (non-ideal) survey environments that must be addressed in an actual survey of a long stretch of rural highway. The extended survey system development process starts by examining the performance problems of a basic survey system applied to the more challenging survey conditions.

Case studies are presented in Chapters 5, 6 and 7. Chapters 5 and 6 present demonstrations of the basic survey system development process, based on archived survey footage kindly provided by the Tasmanian State Government, applied to produce guidepost counting and centreline-marking condition basic survey systems respectively.

Chapter 7 describes the general approach to developing an extended survey system, which may require establishing a supervisory module to monitor changing survey conditions and select survey system procedure options as appropriate. An extended guidepost counting survey system is developed to deal with changing ambient light conditions, and its satisfactory performance under non-ideal conditions confirmed.

A 50 km field trial of the extended guidepost survey system is then presented, and its performance demonstrated to be very good. The field trial was carried out by the author on a section of the national highway in Tasmania, and involved custom mounting a camera on a University of Tasmania vehicle.

Table 8.1 summarises the guidepost survey system performances. The basic guidepost survey system's overall performance on a number of highway sections was 83% under ideal survey conditions, showing that it satisfactorily incorporated the fundamental survey requirements. Under non-ideal survey conditions, the performance of the basic guidepost survey system dropped to 54%, and examination of the reasons for this suggested that changing light conditions were a leading cause of problems in image thresholding and feature identification.

The performance of the extended guidepost survey system applied to the same sections of highway was significantly improved (to 72%), except in the problem area of consecutive image grabs that missed capturing guideposts. This problem was addressed by the version of the extended guidepost survey system used in the 50 km field trial, where performance improved to 88%. The sequential improvement under non-ideal condition, from 54% for the basic survey system, to 72% for the extended survey system used to process archived survey footage, and finally to 88% for the

	Ideal conditions	Non-ideal conditions		
	Basic system	Basic system	Extended system	50 km field trial
Image acquisition	124 posts	196 posts	196 posts	558 posts
- Missed posts	9 (7%)	23 (12%)	27 (14%)	10 (2%)
- Repeated posts	12	3	2	27
Image processing → candidate posts				
- Posts found	106	114	141	510
- Posts not found	9 (7%)	59 (30%)	28 (14%)	38 (7%)
Feature analysis				
- Posts identified	103 (83%)	105 (54%)	141 (72%)	491 (88%)
- Posts not identified	3 (2%)	7 (4%)	0 (0%)	19 (4%)
- Non-posts identified as posts	15	34	28	22
Performance	83%	54%	72%	88%
Confidence level	72%	63%	79%	72%

Table 8.1: Summary of guidepost survey system performances

modified extended survey system used for the 50 km field trial, illustrates the success of the research.

Manual inspections are typically not undertaken in poor survey conditions. Even in good survey conditions, the performance outcome of a manual inspection may only reach around 90%, a value almost achieved by the developed methodology under non-ideal survey conditions.

Under ideal survey conditions, the basic guidepost counting and centreline-marking condition survey systems performed at 83% and 92% respectively. The performance of an extended survey system under such conditions is over 90%, and the extended guidepost counting system's performance was 88% under the 50 km field trial, illustrating the successful outcome of the research.

A caveat to this conclusion is that future survey system development work should include the exercise of surveying the same stretch of highway twice within a short time period, under different survey conditions, to confirm the repeatability of the survey results. In addition, the extended system could be further refined, as outlined in Chapter 7, to achieved an even better performance over manual methods.

The basic centreline-marking survey system's overall performance on a number of highway sections was 92% under ideal survey conditions, showing that it satisfactorily incorporated the fundamental survey requirements. This case study included a demonstration of a follow-on analysis in which an expert system is used to adjust the condition assessment based on consideration of horizontal alignment, whereby the good condition of line-marking is more important on a curved section of road than on a straight section of road.

In conclusion, this research has successfully determined why efforts to more fully automate road feature and condition surveys have, to date, not been successful. It has demonstrated that survey systems for specific applications can be quite easily produced from a generic design approach, inspired by biomimicry, using a two-stage development strategy. The survey systems can be produced using off-the-shelf hardware and software, and the generic design approach lends itself to modularity of the survey system components. In addition, current or near-future computer power should allow multiple survey systems to run in parallel, based on the same stream of live survey images. Such multiple survey systems would probably best be integrated into a master survey system to avoid duplicating some of the image processing work.

An obvious usage of a given survey system is to provide an understanding of how a given rural highway's condition deteriorates over time, by repeating a survey at intervals of (say) six months. This will allow asset managers to better plan highway maintenance work, with potentially large savings in terms of money and crash avoidance. The sequential time series evaluation method would be a straightforward extension to the methodology developed by this research.

8.2 Follow-On Work

Where to from here? Five suggestions are made for follow-on work to build on the research presented in this thesis.

1) **Matlab road survey system toolbox.** A third-party Matlab road survey system toolbox can easily be developed in conjunction with the existing data acquisition, GIS, image processing, neural network and expert system toolboxes. The toolbox should aim to incorporate features of current road survey systems such as GIS/GPS information and user-friendly survey interfaces and databases, and it should aim to provide report-quality output.

2) **Prototype field survey system.** The 50 km field trial presented in Chapter 7 of this thesis has demonstrated that a prototype survey system can be incorporated into a highway patrol vehicle with little effort. This would enable a willing road authority to benefit from initial survey work, such as monitoring the line-marking condition of a specific section of highway; and at the same time provide a platform for refining the survey system towards a commercial product.

As noted, future survey system development work should include the exercise of surveying the same stretch of highway twice within a short time period, under different survey conditions, to confirm the repeatability of the survey results. In addition, it would be useful to carry out a cost comparison study of automated survey systems versus traditional manual surveys.

3) **Advanced survey systems.** There are several areas which promise further improvements in automating road survey systems.

- Increase Matlab's control of the survey camera via the ActiveX interface.
- Incorporate ancillary road information into the survey work.
- Extend the role of the supervisory module, and perhaps incorporate a supervisory module in the basic system. Advanced adaptive learning techniques are discussed in Appendix E, such as reinforcement learning (Sharkey, 1997 & 2002) and self-organising feature maps (Nehmzow, 1996; Rogers, 2000; Touzet, 1997).
- Examine whether stereoscopic processing techniques could significantly improve road survey systems (see Appendix F, and Medioni & Kang, 2004), for example by providing feature distance and size information.

- Examine whether future road survey systems should be based on colour images instead of greyscale information.

4) Biomimicry based research. This research has greatly benefited from the use of biomimicry. It sends a strong message to engineers and scientists of the potential usefulness of considering biomimicry principles when seeking to tackle problems which nature has already solved.

5) Strategy optimisation. Highway management strategy optimisation is an important aspect of asset management. An automated road survey system is of clear benefit in helping to determine optimum asset maintenance work, but artificial intelligence methods may provide additional assistance. In particular, genetic algorithms (see Appendix G, Chan et al., 1994, and Fwa et al., 1994 & 1996) are powerful optimisation tools whose usage by the engineering community is now at about the same point as neural network usage was in the mid-1990s. Matlab has recently released a genetic algorithm toolbox which works in conjunction with its optimisation toolbox, and it is suggested that highway managers seek ways in which these tools might guide the development of complex maintenance strategies.

Perhaps, together with the generic automated survey system design proposed in this thesis, these tools will be able to close the asset management loop cycle (highway construction, condition assessment, funding and maintenance decisions, and renewal strategies) in an even more efficient and effective fashion.

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APPENDIX A PROGRAMMING INTERFACES

Apart from ActiveX, many other protocols are available for the development of programming interfaces (LEADTOOLS, 2004).

COM (Component Object Model) is the underlying architecture that forms the foundation for higher-level software services. It is a technology that enables software to be built in the form of reusable components. The advantage of using COM is that developers can make use of pre-written components rather than developing custom made ones themselves, which makes software development faster and easier. COM objects also include many of features of ActiveX that makes it easy to use, but does not include the extra overhead required by ActiveX.

C++ (Class Libraries) is a general-purpose object-oriented programming language and is intended to be an improved version of *C* with object capabilities. It can be used by developers as a common foundation for building complex applications. It is a user-defined type or abstract data type that encapsulates data and functions which use or process that data. Its objects or classes encapsulate lower level functionality into a higher level interface that facilitates in shortening development time and creating maintainable code. There is a huge variety of comprehensive functionality that can be added to a different software application via *C++* components.

VCL (Visual Component Library) is a framework consisting of classes and components that are used to create applications using Borland Delphi. Delphi has been very successful in the rapid application development (RAD) market, however, many users expressed an interest to Borland for a *C++* RAD tool, called *C++* Builder, which uses an unmodified version of Delphi VCL standard. Part of the power of C++ Builder is the VCL and its components, which makes programming easier, plain and simple. However, there are many programming needs that are not covered by the VCL. Fortunately, a comprehensive selection of third-party software components are available that makes programming as easy as dropping the component onto a form.

.NET is a Microsoft component framework which provides an advanced, high-productivity development environment that features integrated support and deep support for multiple programming-languages. It is a new paradigm of software development for Microsoft because it is not tied to the Windows operating system. The framework is a collection of classes grouped by namespaces that represent the API required to build robust applications and web services. Some third-party software components are available that allow developers to create applications that include comprehensive functionality, and move them from development to implementation more quickly.

DLL (Dynamic Link Library) is a collection of functions, any of which can be called when needed. It offers the most flexibility and the least overhead of the developer interfaces. The advantage of DLL files is that the developer can control if and when a DLL file is loaded into memory (if the development environment has such support) and space is saved in RAM. When a function in a DLL file is needed, the developer can then load the DLL into memory and call the function. Typically, a DLL provides one or more functions that a program accesses either as a static library or as a dynamic link library. A static link remains constant during program execution while a dynamic link is created by the program as needed. A DLL can be used by several applications at the same time. Some DLLs are provided with the Windows operating system and available for any Windows application. Other DLLs are written for a particular application and are loaded with the application.

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APPENDIX B MASKS FOR EDGE DETECTION

Masks for differential gradient edge detection (Davis, 2005)

a. Robert 2×2 operator:

$$R_x = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \qquad R_y = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

b. Sobel 3×3 operator:

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

c. Prewitt 3×3 operator:

$$P_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad P_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

Mask for template matching edge detection (Umbaugh, 2005)

a. Kirsch 3×3 operator:

$$K_0 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \qquad K_{45} = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \qquad K_{90} = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$K_{135} = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \qquad K_{180} = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \qquad K_{225} = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$$

$$K_{270} = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \qquad K_{315} = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

b. Robinson 3×3 operator:

$$R_0 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad R_{45} = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} \qquad R_{90} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$R_{135} = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix} \qquad R_{180} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad R_{225} = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}$$

$$R_{270} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad R_{315} = \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$$

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APPENDIX C EXPERT SYSTEM CASE STUDY

It is generally believed that there is a significant decrease in road safety with the percentage increase of edge break and poor line-marking. In addition, poor road condition on a section with bends further increases the risk to road users. In this case study, road safety is assessed based on the condition of line-marking and edge break, within the consideration of road context.

In brief, each road element is assigned with a score that represents its condition against the related criteria. Table C.1 and Table C.2 show the condition score associated with each criterion taken from ROCOND (1990), for edge break and line-marking respectively.

0	Extreme	: >200 mm average width of fretting
1	Moderate	: 75 - 200 mm average width of fretting
2	Slight	: <75 mm average width of fretting

Table C.1: Condition scores for edge break (ROCOND, 1990)

4	Very good Correct type, width, location No misleading lines visible Line-marking delineation excellent in daylight	1	Poor Misalignment obvious Old misleading lines visible Line-marking delineation poor in daylight (requires repaint)
3	Good Correct type, width, location No misleading lines visible Line-marking delineation good in daylight	0	Very poor Misalignment obvious Misleading lines visible Wrong location or type of line Line-marking delineation inadequate in daylight (overdue for repaint)
2	Fair Correct type, width, location No misleading lines visible Line-marking delineation fair in daylight		

Table C.2: Condition scores for line-marking (ROCOND, 1990)

The condition score ranges from 0 (extreme) to 2 (slight) for edge break, and from 0 (very poor) to 4 (very good) for line-marking. A third score, ranging from 0 (bend) to 4 (straight), is assigned to represent the road geometry. These individual scores are then aggregated to form an overall score, ranging from 0 (low) to 10 (high), which helps in deciding the degree of road safety.

This case study examines the classical approach of aggregating individual condition scores, and compares it with an expert system approach devised by the author.

Classical approach

Traditional scoring systems often use simple mean function to aggregate individual scores. For example, by using the arithmetic weighted mean function, the individual scores ($Score_i$) are aggregated into an overall score (*AggregateScore*), as:

$$AggregateScore = \sum_{i=1}^{n} w_i Score_i \qquad \text{where} \qquad \sum_{i=1}^{n} w_i = 1$$

The weight (w) reflects the relative importance of each issue. By applying the mean function to this case study with a weight of 0.4 for both line-marking and road context conditions, and 0.2 for road edge condition, the degree of road safety (*Safety*) can be obtained from the sum of all individual scores, as:

$$Safety = EdgeBreak + LineMarking + Context$$

where *EdgeBreak* denotes the score for edge condition, *LineMarking* is the score for line-marking condition, and *Context* represents the score for road context. The three scores have ranges of 0-2, 0-4 and 0-4 respectively, which is an implicit incorporation of the weighting factors. A high total score denotes a road section with high safety value, and a low total score denotes a section with low safety.

A mean function has the advantage of simplicity. However, the relationship between the input and output variables is straightforward, which leads to a straight decision surface as shown in Figure C.1. In this figure, the output variable (the overall score

Safety) is plotted as a function of only two input variables (component scores *LineMarking* and *EdgeBreak*), with different weights.

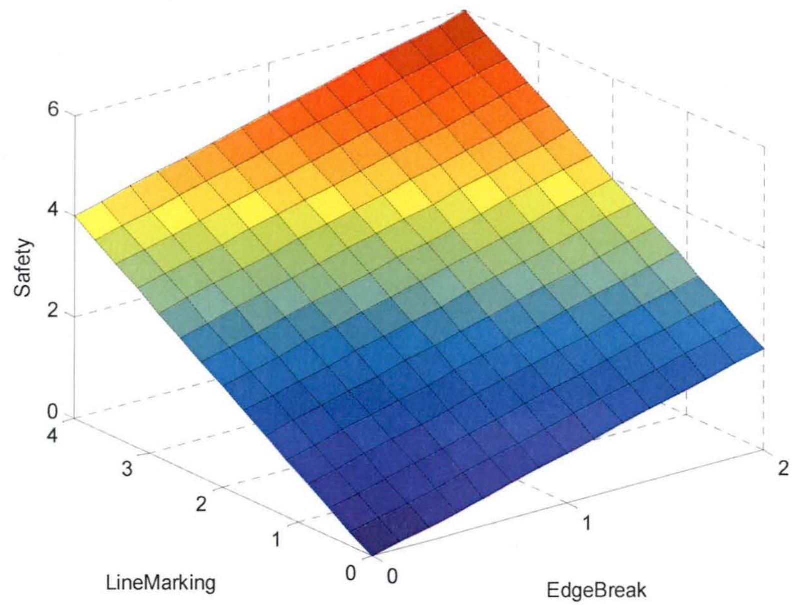

Figure C.1: Traditional linear decision surface

A linear decision surface is perfectly satisfactory for many applications (for example, calculating employee pay cheques from the number of hours worked, and the various pay rates), but for other applications it may fail to adequately describe the relationships between variables.

Considering the example shown in Figure C.1, if the values of both input variables are high, then the value of the output variable, *Safety* (the decision), seems to be reasonable. However, if one input variable has a low value while the other has a very high value, the value of *Safety* is perhaps higher than desirable in the application to hand, with good condition for one element masking the poor condition regarding the other element. Expert systems offer a more elegant solution to this problem.

Expert system approach

Expert rule systems are straightforward to develop, and are better aggregation tools if one or more input scores are low, while others are high. The rules can be written such that any low input score produces a low aggregate score, thus sending a clear message that some aspect of road needs closer attention.

There is no added complexity in developing an expert system, since it uses similar variables defined in the classical scoring system. An expert system developed for this case study contains three input variables (*LineMarking*, *EdgeBreak* and *Context*) and an output variable (*Safety*).

LineMarking is fuzzified by two sigmoid functions (*VeryPoor* and *VeryGood*) and three Gaussian functions (*Poor, Fair* and *Good*), *EdgeBreak* is fuzzified by two sigmoid functions (*Extreme* and *Slight*) and a Gaussian functions (*Moderate*), and *Context* is fuzzified by two sigmoid functions (*Bend* and *Straight*), as summarised in Table C.3. The membership functions used to defuzzify the output variable (*Safety*) are similar to the one used to fuzzify *LineMarking*, but with different names. The value of all variables is between 0 to 10, interpreted as condition ranging from bad to excellent.

	Name	Membership functions
Inputs		
Line-marking	*LineMarking*	*VeryPoor, Poor, Fair, Good, VeryGood*
Road edge	*EdgeBreak*	*Extreme, Moderate, Slight*
Road context	*Context*	*Bend, Straight*
Output		
Road Safety	*Safety*	*VeryLow, Low, Average, High, VeryHigh*

Table C.3: Variables and membership functions

Figure C.2 shows the membership functions used to defuzzify the output variable from a membership degree to a crisp output value. The expert system applies 31 rules. It should be noted that each rule can be associated with a weight (which is separate from the weights used in calculating a weighted mean). After constructing the basic set of rules, much of the development effort for an expert system is devoted to adjusting the rule weights to achieve the desired decision surface.

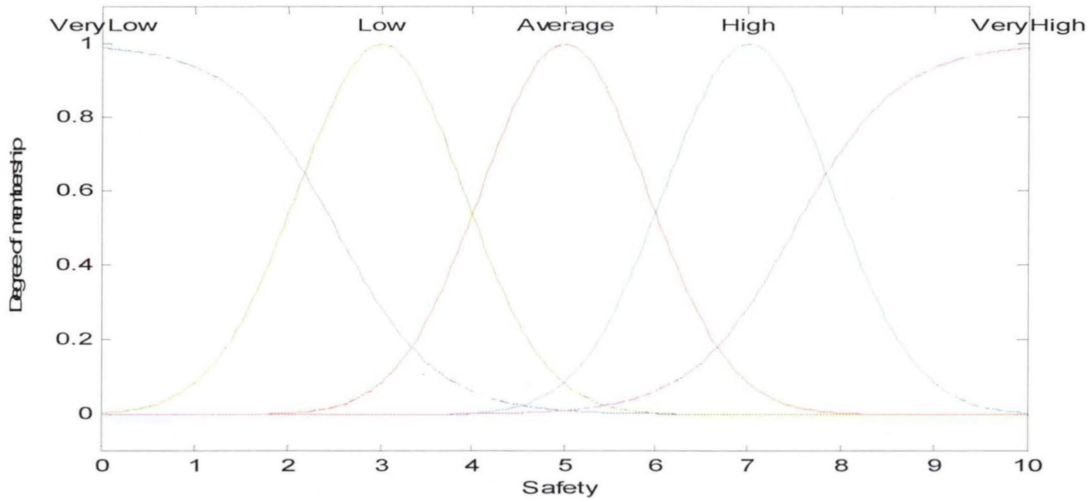

Figure C.2: Membership functions used to defuzzify road safety scores

To illustrate how an expert rule-based system works, consider a simple set of rules as shown in Table C.4. Figure C.3 shows the action of these rules. Consider a set of input values, 6, 8 and 3, for *LineMarking*, *EdgeBreak* and *Context* respectively. These crisp input values (between 0 and 10) are fuzzified through the defined membership functions to the fuzzy degrees of membership between 0 and 1.

IF (*LineMarking* is *Poor*) OR (*EdgeBreak* is *Extreme*) THEN (*Safety* is *Low*)
IF (*LineMarking* is *Good*) AND (*EdgeBreak* is *Moderate*) THEN (*Safety* is *Average*)
IF (*Context* is *Straight*) THEN (*Safety* is *High*)

Table C.4: A set of simple expert rules

The following section uses precise values from the system devised by the author. For the first rule, the input 6 to *LineMarking* is fuzzified by the Gaussian membership function *Poor* (with mean = 4 and standard deviation = 1.2) as:

$$f(x) = e^{\frac{-(x-4)^2}{2\times 1.2^2}} \quad \Rightarrow \quad f(6) = 0.2494$$

while the input 8 to *EdgeBreak* is fuzzified by the sigmoid membership function *Extreme* (with mean = 4 and standard deviation = -1.2) as:

$$f(x) = \frac{1}{1 + e^{-(-1.2)(x-4)}} \quad \Rightarrow \quad f(8) = 0.0082$$

The *OR* operator in this rule is used to select the maximum value among them:

$$\left.\begin{array}{rcccc} LineMarking(Poor) & = & 6 & \rightarrow & 0.2494 \\ EdgeBreak(Extreme) & = & 8 & \rightarrow & 0.0082 \end{array}\right\} \quad OR \quad \rightarrow \quad 0.2494 \quad \rightarrow \quad Performance(Low)$$

Hence, this rule gives a fuzzy degree of 0.2494 for the membership function *Low* of the output variable *Safety*.

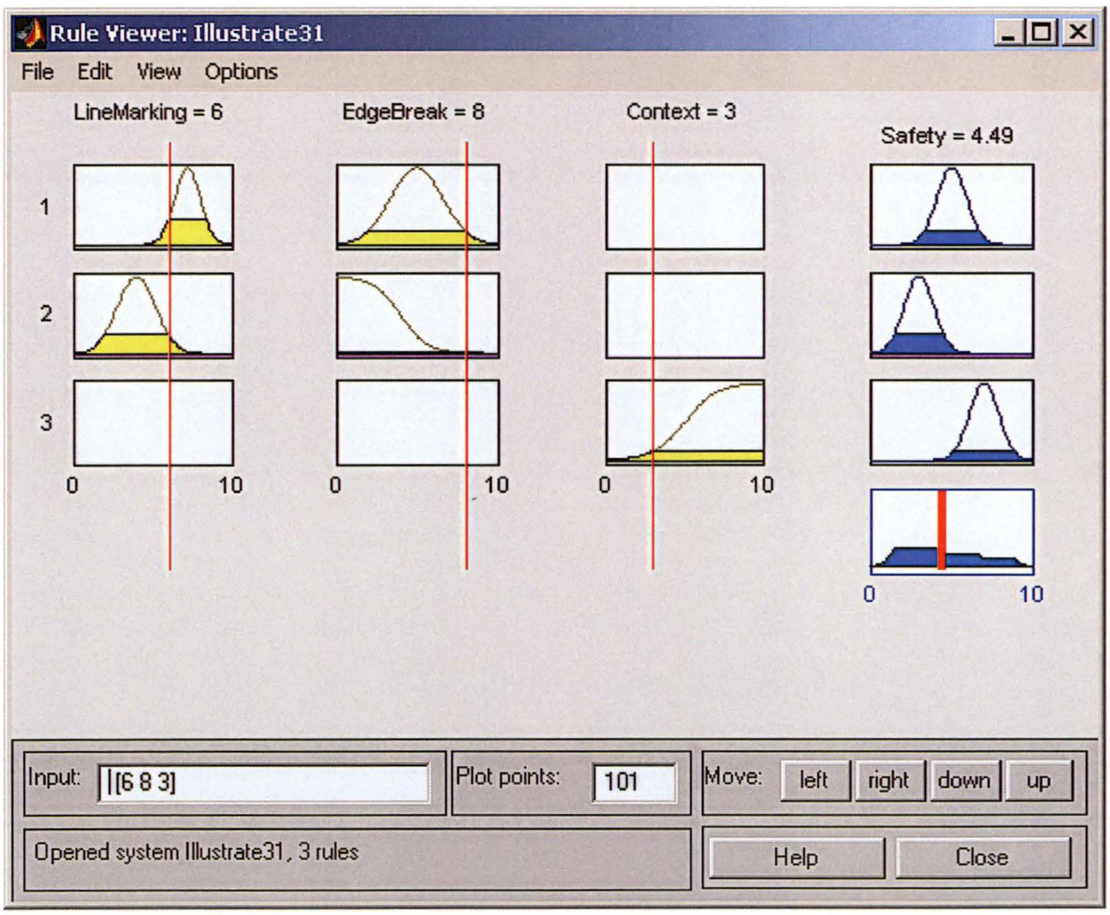

Figure C.3: Rule evaluation

For the second rule, similarly, the input 6 to *LineMarking* is fuzzified by the membership function *Good* into a fuzzy degree of 0.3247, while the input 8 to *EdgeBreak* is fuzzified into a degree of 0.1724, by the membership function *Moderate*. The *AND* operator is then used to select the minimum value among them. Hence, the second rule returns a fuzzy degree of 0.1724 for the membership function *Average* of the output *Safety*.

For the third rule, the input value 3 to *Context* is fuzzified into a degree of 0.1192 by the membership function *Straight*. Since there is only one antecedent in this rule, the degree value to the membership function *High* of the output variable *Safety* is thus 0.1192.

An output fuzzy set (the area under the associated membership function) is then produced for each rule. These fuzzy sets are truncated at the fuzzy degrees of membership obtained for the output variable *Safety* (at *Average* = 0.1724, *Low* = 0.2494, and *High* = 0.1192) by using the THEN operator that acts as the minimum function.

Finally, these output fuzzy sets are summed together and aggregated into a single output membership function. This membership function is then defuzzified by calculating its centroid, where a crisp output value of 4.49 is recovered for the output *Safety*. This may then be identified by the system as being a road section with below average safety.

The weakness of the centroid defuzzification method is that the lowest and highest values of the output variable will respectively be greater than the lowest limit of the universe of discourse, and lower than its highest limit. For example, for the inputs of 0 for all three variables *LineMarking*, *EdgeBreak* and *Context*, the output value for *Safety* is 3.06 instead of 0. Similarly, for the values of 10 for all three input variables, the output value is 6.99 rather than 10. Therefore, these output limits are used to rescale the calculated value (4.49) to the required output range, which gives the true safety index of 3.64.

Figure C.4 shows the decision surface produced by the author using the expert system. The surface is smooth, and is designed to give similar results to the classic weighted mean function if neither input score is poor. However, the rules are written such that if either input variable has a low value (which reflects poor condition), then the output will be low, no matter how high the values of the other input variables.

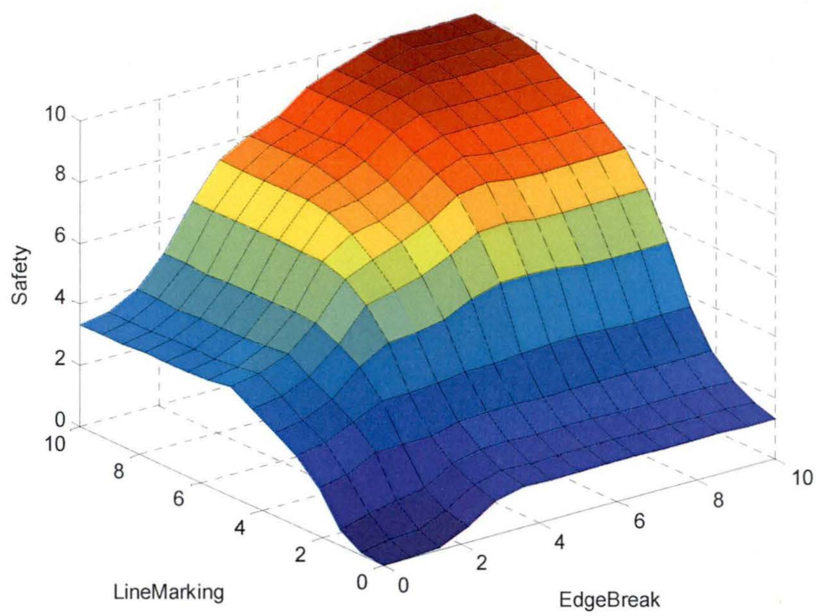

Figure C.4: Decision surface generated using expert system

Comparison of results

By applying the assessment method to the examples in Table C.5, the road safety scores calculated using the classical mean function are compared with the one obtained from the expert system to show the validity of this new approach. Note that since the range of the input values is different between the classical approach and the expert rule approach, Table C.5 shows the input values based on the classical approach. These values are rescaled (to 0-10 scale) before being input into the expert system.

When no input score is low (Examples 1 and 2), the two sets of results obtained are very similar, demonstrating that an expert system can provide an acceptable alternative to the traditional aggregation method.

	Individual Score			Overall Score	
	Line Marking (0 - 4)	**Edge (0 - 2)**	**Context (0 - 4)**	**Classical Approach**	**Expert Rule Approach**
Example 1	3.0	1.3	2.6	**6.9**	**5.8**
Example 2	3.8	1.5	3.5	**8.8**	**9.4**
Example 3	3.8	**0.2**	2.5	**6.5**	**0.5**

Table C.5: Comparison of results

For Example 3, the output value calculated by the arithmetic function denotes an above average degree of safety (6.5). But this does not seem right, and certainly it does not alert the relevant authority to the problem regarding edge condition, especially on a road section which is not straight (Context: 2.5/4). The expert system described above, however produces an overall score of 0.5, which sends a strong message to the authority that some aspect of road condition needs examining.

The expert system can be adjusted to improve its performance. For example, more membership functions can be added, or a different type of function can be used, such as triangular or trapezoidal functions.

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APPENDIX D SUPERVISORY SYSTEMS

Supervisory systems are used in applications whenever a computer is used to supervise the behavior of a continuous-value process. In control-systems literature (Ioannidis et al., 2004), a supervisory system uses available data to characterise the overall system's current behavior, potentially modifying the lower level controllers (such as the basic systems in this research) to ultimately achieve desired specifications. In addition, the supervisory system may be used to integrate other information into the decision-making process. It may incorporate certain user inputs, or inputs from other subsystems. Given information of this type, the supervisory system can seek to tune the supervised controller to achieve better performance.

There has been considerable interest in using supervisory systems theory to develop a systematic framework for the analysis and design of complex engineering systems. Lemmon et al. (1998) introduce some concepts and trends in the applications of supervisory hybrid systems. These systems provide convenient models for a wide range of applications ranging from small real-time embedded systems to large-scale traffic control and manufacturing facilities, and are found to be useful as guiding tools under changing circumstances.

Other applications of supervisory systems are UAVs - unmanned aerial vehicles (Banks, 2000; Butler, 2001; Carmichael et al., 1996; DTIC, 1998) as shown in Figure D.1 (left), deep sea exploration robots, space exploration vehicles (Figure D.1 right), hydraulic network systems (Deltour et al., 2005), and manufacturing processes including offshore industry (Blach, 2005).

Figure D.1: The Altair CU-163301 UAV (AFPA, 2005) - left, and the NASA Mars exploration rover (NASA, 2005) - right

Unmanned aerial vehicles

An example of supervisory systems in the field of unmanned aerial vehicles (UAVs) is Godbole et al. (2000), who use a wavelet-based multi-resolution dynamic maneuver optimisation method to supervise UAVs in route planning and obstacle avoidance. Glassco (1999) also proposes a shared control operation between manual and automatic for UAVs, in which a supervisory system is used to alter flight path to reorient the aircraft to fly towards a target and observe it from a specific range.

Autonomous operation of UAVs requires both trajectory design and tracking tasks to be completely automated. In addition, endurance UAVs are subject to weather considerations, including the impact of operating environment on both the systems reliability as well as air vehicle and sensor performance. Therefore, complex series of automatic flight controllers together with appropriate supervisory logic are required to allow the vehicle to autonomously complete a full mission in the presence of random disturbances such as wind gusts (Clough, 2005; Sonacom, 2000).

Deep sea exploration

Highest-level supervisory systems are used to supervise deep sea robotic vehicles to develop their own learning sequences, thereby reducing the supervision demands on the human operator (von Buchstab, 2005). Labbé et al. (2003) explore the applications of such systems to navigation, guidance and control of an intervention autonomous underwater vehicle, which is capable of simultaneous localisation and mapping, target localisation, and obstacle avoidance in deep sea operation.

Transportation

Adamski (2002) also reviews some knowledge-based supervisory systems used in intelligent transportation systems. Typical examples are Piazzi et al. (2002), who develop a supervisory control scheme for iterative steering of vision-based autonomous vehicles, and Cho et al. (2000) who apply a supervisory control system based on hybrid network models to optimise route guidance in intelligent vehicle highway systems to provide travellers with information minimising the travel time as a kind of advanced traveller information systems. In addition, Hawas (2002a & b) also explain the used of a supervisory control system for advanced traveller information systems and advanced traffic management systems

Manufacturing systems

In the area of manufacturing systems, Lawley & Sulistyono (2002) develop supervisory control policies that allocate resources so that the failure of any given resource does not propagate through blocking to effectively stall other portions of the system. JÉron et al. (2005) explore the use of supervisory control systems to controlling a plant of a system, of which the supervisory system can automatically fixes errors that otherwise would have been discovered by testing and fixed by hand.

Some other applications of supervisory systems to industrial automated manufacturing systems were reviewed in Brandin (1996). In addition, Park & Lim (1998) develop a fault-tolerant robust supervisory control system to guide robots to perform fillet welding under different welding conditions. Another example is Ioannidis et al. (2004), who derive a supervisory controller for scheduling production networks. The supervisory controller is used to tune a set of lower level distributed fuzzy control modules that reduce work-in-process events.

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APPENDIX E OTHER ADAPTIVE TOOLS

Other than the tools described in Chapter 7, there are many other adaptive system strategies that can be applied to improve the flexibility of automated survey systems so that they can adapt to changing survey environment and context. Examples include reinforcement learning strategy, and also advanced neural network techniques such as adaptive learning, competitive neural networks, and self-organising feature maps.

Reinforcement learning

Reinforcement learning, also known as learning by doing, is a methodology that attempts to capture the essence of conditioning. Unlike supervised learning, which requires a trainer to provide the learner with an exact target action in every time step, reinforcement learning is suited to train a neural network for use in unknown environments. The basic idea is to allow the environment to control and train the system, so that the system will learn from its environment (Guha, 1991; Sharkey, 2002; Sharkey & Ziemke, 2001).

In nature, animals learn to associate their behaviours with rewards and punishments. They can be trained to produce an experimenter-required behaviour when they are rewarded for successive approximations to that behaviour. For example, in the early operant conditioning experiments, Skinner (1960) trained rats and pigeons to press levers to obtain food. This was done by giving rewards (food) for desired behaviours and punishments (electric shocks) for undesired behaviours. Similarly, neural network reinforcement learning technique can be use to mimic such animal behaviour in nature, and uses rewards for correct system outputs, and punishments for undesired outputs.

There are numerous examples in the area of robotics where robots are trained using reinforcement learning. Consider a simple example in Sharkey (1997b), in which a robot has to learn to avoid obstacles. At the start it does not need to have any knowledge about the relation between obstacles and sensor information and what actions to take. The robot starts with a random behaviour determined by its randomly initialised network and the sensor signals. As a result it will explore the environment and bump into obstacles.

Reinforcement learning is used to train the robot to avoid obstacles, by which whenever a bump occurs, the last action is evaluated as undesired and a "punishment" is given. So rather than specifying the exact values to be sent to the motors, the evaluator simply tells the control structure whether the action was right or wrong. This signal then has to be used by the learning rule so that the number of future punishments is minimised. If this is applied in the right way, the obstacles avoidance behaviour of the robot improves by experience.

It is relatively easy to detect undesired actions such as bumps. The robot can be equipped by whiskers so that it can detect obstacles. In this case, the evaluation function can be implemented as an instinct rule allowing the robot to learn completely autonomously. In addition, in order to speed up the learning process, advanced methods have been developed to give the robot immediate evaluation for each action. Examples are such as delayed reinforcement, also known as Q-learning, and shaping, which adds an explicit trainer that provides step-by-step guidance.

Another example is the vision-arm system, which creates its own training data by moving in space (Rathbone & Sharkey, 1999; Sharkey, 1997a). The neural network controller takes input from a two-camera vision system and the output controls the arm movement. All movements are added to the training data whether or not they represent successes or failures to pick up a target. For failure, punishments are given, and the actual move and the motor commands are updated to the training data for use with backpropagation. After each move, the controller is batch trained on a sequence of randomly selected training sets. Then the arm is again moved by the controller and the process is repeated until the object is picked up.

In order to allow for a maximum of robot autonomy, it is often desirable to reduce designer intervention to a minimum of feedback and instruction. Also, it is often not even possible to provide a robot with an exact target output in every time step, for much the same reason why it is impossible to tell a child learning to ride a bike how exactly to move its legs, arms, and body at every point in time. For such tasks, the robot, much like the child, simply has to figure out for itself how exactly to solve a problem, and how to organise and adapt its sign processes in interaction with the environment. Hence, robots for complex tasks are typically not trained using supervised learning techniques, but are often trained using reinforcement learning.

Adaptive learning

Instead of completely engineering an automatic assessment system for a specific task, it can be trained using incomplete data and then rely on the generalisation characteristics of its neural network to adapt to novel and unpredictable changes in the world. The analogy to this is that the systems have to learn something which they should already know.

Neural networks can be designed with adaptive learning so that they can be adjusted at each time step based on new input and target vectors. This allows them to respond to changes in environment as they are operating. This technique has been applied to areas with dynamic environment, such as error cancellation, signal processing, and prediction in robotic, control and communication systems (Yang & Linkens, 1994; Zhou et al., 2000). In fact, real-time neural control systems that make no distinction between a learning and a performance phase are promising candidates for the control of adaptive behaviour (Sharkey & Heemskerk, 1997).

Sharkey (1998) and Ziemke & Sharkey (2001) review some techniques of adaptive learning used in robotics applications, including obstacle avoidance, garbage recycling, maze learning, following the trainer, playing fetch, controlling walking and turning, driving a road vehicle, operating a disembodied arm, deciding on landmarks, localising, and wandering. The motivation is to use the work from natural systems as an unconstraining inspiration.

A good example is the Mobile Adaptive Visual Navigator (MAVIN), which utilises a number of adaptive neural networks for learning and performance at several stages.

It is designed to learn various motor behaviours and is required to associate these with learned objects. The building blocks for visual object learning, behavioural conditioning and so on are based on modular neural network paradigms such as Adaptive Resonance Theory (ART), which calls for implementation in hierarchical structures that consists of many processing levels. The actions of MAVIN are dependent on the robot's internal state that keeps a little history of the former actions.

Competitive neural networks

The main property of a neural network is an ability to learn from its environment, and to improve its performance through learning. Competitive networks are a type of neural networks that learn to categorise the input vectors presented to it using competitive learning, which is another type of unsupervised learning method. A competitive network contains only a single layer, called a competitive layer. During learning, the neurons in the competitive layer distribute themselves and learn to recognise frequently presented or groups of similar input vectors automatically.

During training each neuron in the layer compete among themselves to be associated with a specific input vector. This is done by adjusting its weight vector toward the input vector, with methods such as the Kohonen learning rule, which is useful in recognition applications since it allows the weights of a neuron to learn an input vector. The neuron whose weight vector was closest to the input vector is updated to be even closer. The result is that the associated neuron is more likely to win the competition the next time a similar vector is presented, and less likely to win when a different input vector is presented.

A competitive network is designed such that the competitive transfer function accepts a net input vector for the competitive layer and returns neuron outputs of 0 for all neurons except for the neuron associated with the net input. This neuron's output is 1. Eventually, if there are enough neurons, every cluster of similar input vectors has a neuron that outputs 1 when a vector in the cluster is presented, while outputting a 0 at all other times. Thus, the network learns to categorise the input.

Competitive networks also learn the distribution of inputs by dedicating more neurons to classify parts of the input space with higher densities of input. However, the classes that each neural network finds are dependent only on the difference between input vectors. If two input vectors are similar, the competitive layer might put them in the same class. Unfortunately, there is no mechanism in a strictly competitive layer design to say if any two input vectors are in the same class or different classes.

Self-organising neural networks

Our brain is dominated by the cerebral cortex, a very complex structure of billions of neurons and hundreds of billions of synapses. Each type of neurons are responsible for different human activities, and thus associated with different sensory inputs. Each sensory input is mapped into a corresponding area of the cerebral cortex. The cortex is a self-organising computational map in the human brain.

A class of neural networks, called self-organising networks, has been developed to mimic the function of the cortex in the human brain. They are based on competitive learning. In fact, self-organising in networks is one of the most fascinating topics in the neural network field. Such networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly (Demuth & Beale, 2003; Rogers, 2000).

In nature, representations of objects maybe considered to be states or patterns of neural activity in the brain. Each time a neural pathway is used, there is a metabolic change in the synaptic connection between the neurons in the path that facilitates subsequent signal transmission. The more often two neurons are used together, the stronger will be their strength of connection and the greater the likelihood of one activating the other. The synaptic connections come to represent the statistical correlates of experience. Thus in learning to recognise objects, groups of neurons from many areas of the brain are linked together to form assemblies (Negnevitsky, 2001). Self-organising networks are in fact designed to mimic this principle.

Again in contrast to supervised learning, self-organised learning does not require an external teacher. During training, the neural network receives a number of different input patterns, discovers significant features in these patterns and learns to classify them into appropriate categories. It tends to follow the neuro-biological organisation of the brain, and aims to learn rapidly. In fact, self-organising networks learn much faster than back-propagation networks, and have more potential to be used in real time. Thus, they are effective in dealing with unexpected and changing conditions.

A special type of self-organising network is the Kohonen self-organising feature maps (SOFMs), which was introduced by Teuvo Kohonen in late 1980s as a special class of neural networks, based on his principle that the spatial location of an output neuron corresponds to a particular feature of the input pattern. SOFMs learn to classify input vectors according to how they are grouped in the input space, and learn the distribution of input vectors. They allocate more neurons to recognise parts of the input space where many input vectors occur and allocate fewer neurons to parts of the input space where few input vectors occur.

SOFMs also learn the topology of their input vectors in such a way that neurons physically near each other in a layer respond to similar input vectors. The layer of neurons can be imagined to be a rubber net that is stretched over the regions in the input space where input vectors occur. When a vector is presented during learning, instead of updating the weights of only the associated neuron, SOFMs update the weights of the neuron and its neighbours. The result is that neighbouring neurons tend to have similar weight vectors and to be responsive to similar input vectors.

Hence, SOFMs differ from competitive layers in that neighbouring neurons in the networks learn to recognise neighbouring sections of the input space. They can learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on. As SOFMs allow neurons that are neighbours to the winning neuron to output values, the transition of output vectors is much smoother than that obtained with competitive layers, where only one neuron has an output at a time.

Self-organising neural networks find application in the preprocessing of raw sensory information because of the feature detection characteristics. When exposed to large data sets, they will organise themselves in such a way that similarities in the data are detected by the neural network. Data sharing similar features are clustered on neural units that are ordered so that neighbouring units represent similar clusters. This method is often used for down scaling the dimensionality of large data sets.

For example, Nehmzow (1996) reports experiments where a robot explores its environment while constructing an internal representation of its world with a SOFM. The robot does not use any knowledge from supervisors or built-in programs. After the initial self-organisation phase, the internal representations are successfully used for tasks such as localisation and decision-making based on visual data. Another example is reported by Touzet (1997), who shows that nearby nodes in a SOFM represent similar real-world features such as certain obstacles.

Learning vector quantisation networks

Learning vector quantisation (LVQ) is a method for training competitive layers in a supervised manner. Unlike competitive layer, LVQ networks learn to classify input vectors into target classes chosen by the user. They contain two layers: a first competitive layer and a second linear layer. The competitive layer learns to classify input vectors into subclasses in much the same way, while the linear layer transforms the competitive layer's classes into target classifications defined by the user.

LVQ networks can classify any set of input vectors. The only requirement is that the competitive layer must have enough neurons, and each class must be assigned enough competitive neurons. To ensure that each class is assigned an appropriate amount of competitive neurons, it is important that the target vectors used to initialise the LVQ network have the same distributions of targets as the training data the network is trained on. If this is done, target classes with more vectors will be the union of more subclasses.

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APPENDIX F STEREOSCOPIC PROCESSING

In a single view of a scene, it is normally impossible to deduce absolute sizes as all the objects and their depths can be scaled up or down by arbitrary factors, which cannot be discerned from a monocular view. An obvious characteristic of the human visual system is that it employs two eyes that face forward so that their fields-of-view overlap, forming a binocular or stereo vision which permits depth to be discerned within a scene, allowing one to judge the relative distance to objects (Davies, 2005).

Human stereoscopy

Within a fairly short range of depths, humans are able to use the slight differences in the images of the world that are seen by the two eyes to estimate the distance to points on an object and thus the object's shape. Similarly to other aspects of human vision, stereoscopy is primarily comparative. The mechanism involves recognising the object in the two scenes and comparing the angles of vergence required to fuse the images. The change of vergence angle of the eyes as one shifts attention from one feature to another also indicates to the brain which one is closer (Russ, 2002).

Although humans do not measure distances, this is possible for a computer vision system, as depth information can be obtained from pairs of stereo images, which are two images of the same scene taken from slightly different viewpoints. This allows the salient surfaces in a three-dimensional space to be extracted (Medioni & Kang, 2004).

Viewing stereo pair images provides the same visual cues to the eyes and produces the same interpretation. In human stereoscopy, the relative distance to each feature identified in both the left and right eye views is given by the differences in the vergence angles by which the eyes must rotate inward to bring each feature to the central fovea in each eye. Actual distance of a feature can therefore be measured using the different parallax displacements of the feature in two stereo images of the scene.

Stereo vision model

To implement a stereo vision system by mimicking the human stereoscopy, two cameras are required to be mounted such that their optical axes are parallel and the image planes are coplanar, as shown in Figure F.1 (Starck et al., 1998).

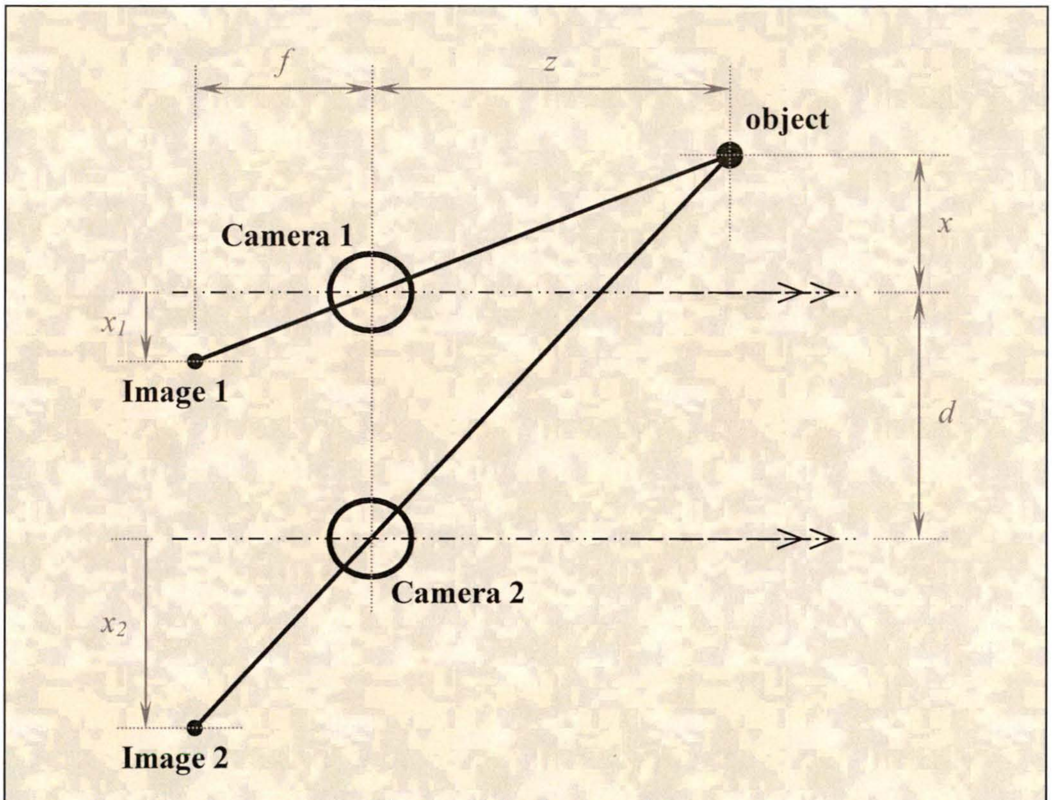

Figure F.1: Stereo vision

In Figure F.1, d denotes the distance between the two cameras. Image 1 and Image 2 are images of the object seen in the two cameras correspondingly, and, as noted, these images locate at a distance f from the origin of the cameras. f is also known as the focal length of the lenses of these cameras (assuming that both cameras have the same focal length). z is the actual distance of the object from the viewpoint. In addition, x_1 and x_2 are the corresponding distances of Image 1 and Image 2 from the optical axes of Camera 1 and Camera 2 respectively.

Based on the principle of similar triangle,

for Camera 1, $\frac{x}{z} = \frac{x_1}{f}$ and for Camera 2, $\frac{x+d}{z} = \frac{x_2}{f}$

Subtracting these two equations gives $\frac{d}{z} = \frac{x_2 - x_1}{f}$

and the actual distance of the object can be found as $z = \frac{df}{x_2 - x_1}$

In the above equations, (x_2 - x_1), known as disparity, is the difference in images induced by the relative displacement of the two stereo cameras. Disparity is a very general property of images, and is useful for image understanding. It is important because it contains enough information to allow a partial reconstruction of the three-dimensional structure of the scene from its two-dimensional projections. Disparity may be represented by a vector field mapping one image onto the other, and can be interpreted into meaningful statements about the scene, such as depth and shape. For example, the position disparity between image pairs determines the depth of a scene captured by the dual camera system (Laplante & Stoyenko, 1996; Morris, 2004).

Applications of stereo vision

The utility of a stereoscopic view of the world to communicate depth information has resulted in the use of stereo cameras to produce "stereopticon" slides for viewing, which was very popular more than 50 years ago. More recently, real-time stereo vision systems have been available and applied to many areas in conjunction with tools like neural networks (Zhao & Thorpe, 2000).

In the area of urban traffic monitoring, Curio et al. (2000) review some application of stereo vision systems to pedestrian detection. They also present a binocular vision system to increase the detection performance of short distance field. In addition, Fang et al. (2002) describe the use of binocular stereo vision systems on intelligent vehicles to deal with depth-based image segmentation and object detection problems.

It is believed that stereo vision systems have the potential to be applied to automated visual survey and assessment that involve the need to consider feature distances and depths. For guidepost counting as an example, stereo vision could be useful when dealing with images containing irrelevant guideposts or other objects at the background, as shown in Figure F.2.

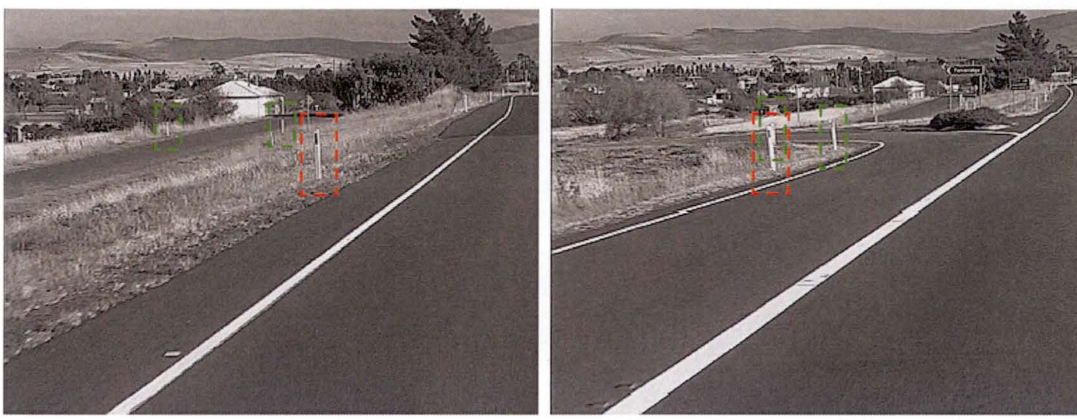

Figure F.2: Irrelevant guideposts at the background

In Figure F.2 (left), the road image contains some guideposts along the local road located at the back of the highway. These guideposts are irrelevant to the main highway being surveyed, and should not be counted. However, a basic guidepost counting system as the one presented in Chapter 5 will normally count all three guideposts, which is unreliable. Therefore, stereo vision can be applied to identify the distance of each guidepost found, and ignores those far guideposts, as well as other objects that looked like guideposts. In the right figure, a guidepost is blocking another one at the back, which will lead to mis-counting. Again, stereo vision can be applied to overcome the issue.

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APPENDIX G STRATEGY OPTIMISATION

Strategy optimisation is important to infrastructure asset management, especially in determining the optimal condition for asset maintenance or treatment, as it is useful in reducing long-term maintenance costs and getting the most benefit or gain in asset life. It is also useful in determining the optimal distribution of funding to achieve the best possible future asset condition, and the optimal use of resources to cover the maximum asset network in a planning period.

Road management strategy

A road asset management strategy presents a set of programmed management actions to achieve asset performance objectives based on economic benefit, funding levels, community service obligations, and sustainable development objectives (Austroads, 1994). It aims to provide sustainable road asset replacement whilst maintaining an overall acceptable level of service within the financial resources available (GMS & ASDCS, 2001).

Road condition and performance can assist in determining treatment strategy options in the life of the asset. They can be used to develop optimal strategies that deliver the best value for money. However, the best order in which to carry out various maintenance or renewal projects may not be obvious, especially if projects have near-equal priority. Final decisions are often based on the "squeaky wheel" principle, but while decisions may satisfy the politics of the moment, they may not produce the optimal application of resources. Defensible strategy optimisation techniques therefore are required to support decisions, such as determining the long-term funding needs based on current service levels and condition (Prabhu, 2002).

Optimisation

Optimisation is the process of achieving objectives (to maximise outputs) by determining the best of a range of options. It is different from ranking as ranking is based on a constrained range of options. In asset management, an optimal solution is usually based on the cost of the solution, the asset condition and the network coverage. Information required in an optimisation analysis include the available options (such as asset treatments), the relative merits of each option (such as treatment effectiveness) and the costs of each option (treatment costs).

Optimisation methods in the sense of identifying best-fit curves are well understood. However, the traditional approaches to multi-objective optimisation problems, such as game theory, and goal attainment, have not enjoyed much use in asset management. Part of the problem appears to be that the conditions under which a classical optimisation method is appropriate are often too artificial and restrictive to be easily applied to an asset management situation. Put another way, knowing how to solve the classic optimisation problem of establishing the best order in which a salesman should visit cities does not appear to help an asset manager much, even though the problem is superficially similar.

Some examples of current optimisation techniques applied to asset management are given by Wang & Liu (1997), who use fuzzy set theory to optimise road pavement performance through effectively utilise an allocated budget. In addition, Kleiner (2001) also reviews some decision tools used to optimise decisions regarding renewal, inspection, and condition assessment of infrastructure assets.

Genetic algorithms

Evolution is a tortuously slow process from the human perspective, but the simulation of evolution on a computer does not take billions of years. The evolutionary approach to machine learning is based on computational models of natural selection and genetics. This is called evolutionary computation, which simulates evolution on a computer by using the processes of selection, mutation and reproduction. This iteratively improves the quality of solutions until an optimal, or at least feasible, solution is found. The result of such a simulation is a series of optimisation algorithms, usually based on simple rules.

Genetic algorithms, introduced by John Holland in the early 1970s, is one of the evolutionary computation techniques. They provide robust and reliable solutions for highly complex, non-linear search and optimisation problems that previously could not be solved at all. They are also proved to be more efficient and much simpler than traditional heuristic algorithms in solving bi-level models and achieving the global optimum solution (Yin, 2000).

Genetic algorithms are optimisation methods based on the "survival of the fittest" principle of natural selection. To appreciate the basic idea, consider a number of animals that are somehow able to interbreed and produce offspring. Let the fitness of an animal to fill a certain ecological niche be judged in terms of the animal's speed, strength, intelligence, and ability to kill prey. After a number of generations, we would expect convergent evolution to result in the population of animals all being variations on the same design: tigers, lions, cheetahs, and jaguars.

A genetic algorithm seeks to mimic this process, starting off with a number of acceptable possible solutions, and evolving the solutions through a number of generations according to a fitness function. This is intuitively pleasing, and avoids the need for complex mathematics. Figure G.1 shows the algorithm in outline, starting with a population of initial solutions. Each solution contains a set of decision variables encoded as a "chromosome", which is usually a binary string code. Applied to asset management, the decision variables might be each project's priority (or its cost-benefit ratio), and the amount of people and equipment needed.

The second step is to define a fitness function to assess the performance of individual solutions. A fitness function is an evaluation function which is used to measure the chromosome's performance, or fitness, for the problem to be solved. A genetic algorithm uses a measure of fitness of individual chromosomes to carry out reproduction.

As reproduction takes place, pairs of chromosomes are selected for mating, with preference given to better solutions. Crossover and mutation operators are applied to create offspring, with the crossover operator exchanging parts of two single chromosomes, and the mutation operator changing the gene value in some randomly chosen location of the chromosomes. The mutation operator is acting to mimic the process by which nature introduces new features into animals that are evolving (bigger teeth, for example).

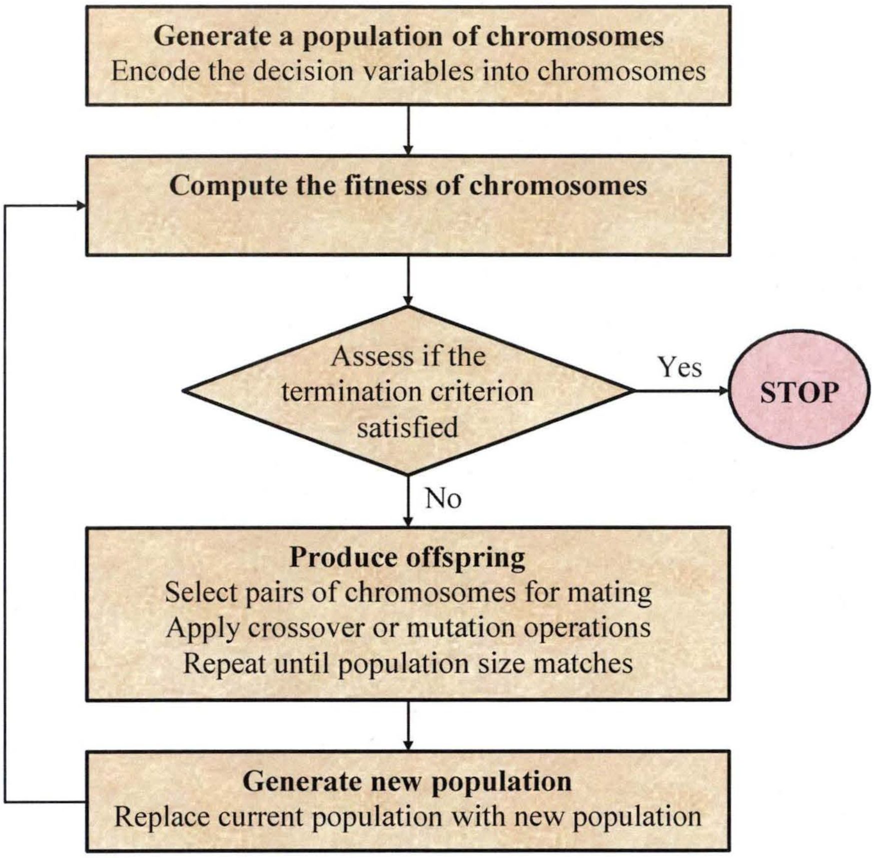

Figure G.1: The genetic algorithm

After a number of successive reproductions, the less fit chromosomes become extinct, while those best able to survive gradually come to dominate the population. New generations are produced until a population of solutions results that satisfies the termination criterion, which is typically an acceptable overall fitness. The final population should then contain a set of solutions all of which are optimal or near optimal.

Encoding variables into chromosomes, and defining a fitness function, are sometimes not easy tasks, but genetic algorithms offer an optimisation approach that can handle complex situations beyond the reach of conventional methods.

Applications of genetic algorithms to road management

Genetic algorithms have been applied to many areas such as transport and road traffic management. A common application of genetic algorithms to transport management is to optimise urban transit network design by searching for the best routes and associated frequencies for the desired objective, and at the same time minimising the overall cost (Pattnaik et al., 1998; Chien et al., 2001; Bielli et al., 2002; Ngamchai & Lovell, 2003; Tom & Mohan, 2003). Genetic algorithms have also been used to optimise the schedule of urban transit network (buses and trains) in order to reduce the problems of delay, congestion, and environmental pollution due to these services (Chakroborty & Subrahmanyam, 1995; Shrivastava & Dhingra, 2002).

Other applications of genetic algorithms to transportation planning include Kalić & Teodorović (2003), who use a genetic algorithm to search for the best fuzzy rule for travel demand prediction; and Charypar & Nagel (2005), who use genetic algorithms to construct all-day activity plans. In addition, Yang et al. (2004) also present a genetic algorithm design for the route choice of public transit passengers by taking the psychology of public transit passengers into account.

In the area of road traffic management, the most common application of genetic algorithms is traffic flow prediction (Baek et al., 2004). For example, in some applications that involve the use of neural networks for traffic flow modelling and forecasting, genetic algorithms are used to optimise the structures and to search for the best architectures for these neural networks (Vlahogianni & Karlaftis, 2004; Abdulhai et al., 2002; Zhong et al., 2004 & 2005; Vlahogianni et al., 2005). Another example is the use of genetic algorithms by Cheu et al. (1998) to search for parameter values associated with the simulation of expressway traffic flow in Singapore.

Other applications of genetic algorithms to road traffic management include scheduling of multiple lane closures to minimise a network's total traffic delay (Ma et al., 2004), calibrating the driving behaviour parameters of a microscopic traffic simulation model (Yu et al., 2004), and solving dynamic optimisation problems of road network signal control (Girianna & Benekohal, 2004). In addition, Lingras (2001) also shows that genetic algorithms can better classify highway sections based on temporal traffic patterns compared to a conventional statistical method.

Genetic algorithms have also been applied to many other areas such as air transportation (Gu & Chung, 1999; Pulugurtha & Nambisan, 2001a & b) and vehicle detection (Sun et al., 2005), and are found to be more effective than experienced professionals.

In infrastructure asset management, Chan et al. (1994 & 2003) and Fwa et al. (1994 & 1996) provide some examples of genetic algorithm approaches to several applications, such as optimising the allocation of funds to road agencies, and solving the pavement maintenance and rehabilitation trade-off problem. They also examine the ineffectiveness of traditional optimisation approaches, such as formula-based (based on fixed criteria) and need-based approaches. In addition, Liu et al. (1997) also use genetic algorithms for cost optimisation of long-term maintenance strategy of bridge systems.

These examples show the potential of genetic algorithms in solving optimisation problems. Although there are not many existing applications of genetic algorithms to road infrastructure management at the present time, it is believed that such tools are useful and have the potential in optimising road management strategies, especially when applied in conjunction with the road feature condition data obtained through condition assessment.

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